

Cyclists' hazard anticipation and performance

Kovacsova, Natalia

DOI

[10.4233/uuid:f6532019-84a8-40b3-8dfa-1176c97d57c1](https://doi.org/10.4233/uuid:f6532019-84a8-40b3-8dfa-1176c97d57c1)

Publication date

2020

Document Version

Final published version

Citation (APA)

Kovacsova, N. (2020). *Cyclists' hazard anticipation and performance*. [Dissertation (TU Delft), Delft University of Technology]. <https://doi.org/10.4233/uuid:f6532019-84a8-40b3-8dfa-1176c97d57c1>

Important note

To cite this publication, please use the final published version (if applicable).
Please check the document version above.

Copyright

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy

Please contact us and provide details if you believe this document breaches copyrights.
We will remove access to the work immediately and investigate your claim.



COLLISION



NEAR MISS



SAFE
SITUATION

Cyclists' hazard anticipation and performance

Natália Kováčsová

Cyclists' hazard anticipation and performance

Natália Kováčsová

Cyclists' hazard anticipation and performance

Dissertation

for the purpose of obtaining the degree of doctor

at Delft University of Technology

by the authority of the Rector Magnificus, prof.dr.ir. T.H.J.J. van der Hagen,

Chair of the Board for Doctorates

to be defended publicly on

Friday 17 April 2020 at 12:30 o'clock

by

Natália KOVÁCSOVÁ

Master of Science in Psychology, Comenius University in Bratislava, Slovakia

born in Galanta, Slovakia

This dissertation has been approved by the promotor.

Composition of the doctoral committee:

Rector Magnificus	chairperson
Dr. ir. J.C.F. de Winter	Delft University of Technology, promotor
Prof. dr. M. P. Hagenzieker	Delft University of Technology, promotor

Independent members:

Prof. dr. T. J. Lajunen	Norwegian University of Science and Technology
Prof. dr. D. Twisk	Queensland University of Technology
Prof. dr. D. de Waard	University of Groningen
Prof. dr. G. P. van Wee	Delft University of Technology
Prof. dr. ir. D. A. Abbink	Delft University of Technology, reserve member

Other members of the doctoral committee:

Dr. ir. R. Happee	Delft University of Technology
-------------------	--------------------------------



This research was performed within the People Programme (Marie Curie Actions) of the European Union's Seventh Framework Programme FP7/2007-2013/under REA grant agreement n° 608092.

Cover design by Tanja Russita

© 2020 Natália Kováčsová

All rights reserved. No part of the material protected by this copyright notice may be reproduced or utilized in any form or by any means, electronic or mechanical, including photocopying, recording or by any information storage and retrieval system, without written permission.

CONTENTS

	vii	Summary
	xi	Samenvatting
1	1	General introduction
2	11	Cyclists' eye movements and crossing judgments at uncontrolled intersections: An eye-tracking study using animated video clips
3	35	What will the car driver do? A video-based questionnaire study on cyclists' anticipation during safety-critical situations
4	61	Emergency braking at intersections: A motion-base motorcycle simulator study
5	85	Riding performance on a conventional bicycle and a pedelec in low speed exercises: Objective and subjective evaluation of middle-aged and older persons
6	115	Cycling Skill Inventory: Assessment of motor-tactical skills and safety motives
7	123	PC-based hazard anticipation training for experienced cyclists: Design and evaluation
8	153	Discussion and conclusions
	167	Acknowledgments
	171	List of publications
	175	Curriculum vitae

SUMMARY

Two-wheeler vehicles (i.e., bicycles, mopeds, and motorcycles) are becoming increasingly popular in congested cities because of their small dimensions, low cost of use compared to cars, and their contribution to a healthy lifestyle. Even though the use of two-wheelers offers benefits, their low conspicuity, instability, and vulnerability of the users create safety risks. Due to their small size, two-wheelers tend to be overseen by other road users, especially at intersections. Furthermore, the stability of two-wheelers is easily affected by disturbances such as an uneven road surface. Moreover, the unprotected state of two-wheeler users contributes to a high risk of serious injuries once an accident happens. A better understanding of how crashes occur in the rider-vehicle-road system is needed.

The research in this dissertation focuses on the cognitive and motor performance of two-wheeler users in safety-critical situations. Experiments were conducted among conventional cyclists, users of electric bicycles, and motorcycle users. An electric bicycle is a relatively new type of vehicle that has been adopted particularly by older people. This uptake creates an additional safety risk as older people are a vulnerable group in traffic because of their physical frailty.

The first scope of this dissertation concerns the investigation of cyclists' hazard anticipation performance and the examination of whether hazard anticipation performance can be enhanced with a short training intervention. The following two research questions are addressed:

- 1) Which situational and individual factors influence cyclists' hazard anticipation performance in safety-critical situations at intersections?
- 2) How does a training intervention affect cyclists' hazard anticipation performance and perceived risk?

The second scope of this dissertation concerns the investigation of two-wheeler users' riding performance and their self-assessments in critical intersection situations and in low-speed tasks. The following two research questions are addressed:

- 3) How are two-wheeler users' characteristics at the strategic and tactical levels associated with braking performance in safety-critical intersection situations?
- 4) How does cycling performance in low-speed tasks differ between riding an electric bicycle and riding a conventional bicycle?

In Chapters 2–4, two-wheeler users' hazard anticipation skills and braking performance in safety-critical intersection situations were investigated. First, in **Chapter 2**, cyclists' eye movements and crossing judgments at a 4-way uncontrolled intersection were examined using animated video clips. The eye-tracking results showed that cyclists gazed at the approaching car when it was relevant to the task of crossing the intersection and posed an imminent hazard; the cyclists directed virtually no attention to the approaching car after it had stopped or passed the intersection. The effect of cycling speed (15, 25, or 35 km/h) on cyclists' eye movements and crossing judgments was only small. This study demonstrated how cyclists' eye movements and crossing judgments

are affected by situational factors, but it remained to be investigated which visual cues guide hazard anticipation and braking performance.

A video-based survey study presented in **Chapter 3** aimed to understand which visual cues contribute to cyclists' correct and incorrect predictions of car driver's right-of-way violation at an intersection, and which factors contribute to cyclists' self-reported slowing-down behavior. The results showed that cyclists' predictions of the driver's action develop over time: the predictions were the most accurate when the time to the conflict was shortest. Both bottom-up (e.g., the speed of the car) and top-down cues (e.g., traffic rules and previous experience) were found to affect cyclists' predictions of what the driver will do. Cyclists who indicated that the car's speed was high or that the car was accelerating were more likely to correctly predict that the driver will not let the cyclist cross first. On the other hand, cyclists who indicated that the car's speed is low, that the car is decelerating, or that the cyclist has the right of way were more likely to falsely believe that a driver will yield to the cyclist. Correct predictions of drivers' right-of-way violation and high perceived risk were associated with self-reported slowing down behavior.

After having studied users' hazard anticipation skills, it still remained to be investigated whether two-wheeler users are able to perform a braking maneuver to avoid a crash in case a car driver does not yield. Therefore, a motorcycle simulator study (**Chapter 4**) was set up to examine how riders brake in impending-crash, near-miss, and safe intersection situations. The car's direction of travel (coming from the opposite direction vs. coming from the right), the car's motion (continuing straight, beginning a left turn and stopping, turning left), and the car's indicator lights (on vs. off) were manipulated. The results showed that although riders braked in the majority of trials when the car crossed their path, they were still often unsuccessful in avoiding a collision with the car. The emerging conclusion from these studies is that, if a car driver violates the traffic rules at an intersection, it may be impossible for the two-wheeler user to avoid a crash.

Crash statistics indicate that users of electric bicycles are more often involved in single-bicycle crashes than riders of conventional bicycles, suggesting that users of electric bicycles have difficulty in maneuvering tasks. In **Chapter 5**, riding performance on a conventional and electric bicycle in three low-speed tasks for which stabilization skills are known to be important was examined for middle-aged and older cyclists. The low-speed tasks were: low-speed cycling at approximately 7 km/h, accelerating to a speed of 17 km/h, and a shoulder check during which a cyclist was asked to indicate a direction with the left hand and look over the left shoulder. The results showed that during low-speed cycling and shoulder check tasks, older people show additional steering input and more roll motion compared to middle-aged cyclists. Thus, although electric bicycles provide benefits to older persons, older persons experience difficulties at the operational level and may, therefore, benefit from new technologies helping them to execute particular tasks. Electric bicycles allowed cyclists to accelerate faster to cruising speed compared to conventional bicycles.

In Chapter 5, participants completed a Cycling Skill Inventory (CSI), a questionnaire that measures subjective cycling skills. The results showed only small correlations

between cyclists' self-assessed skills and their actual performance during the low-speed tasks. These small correlations could be explained by the fact that the CSI questionnaire assesses a variety of skills whereas the field experiment focused solely on motor skills. Because limited knowledge exists on self-assessment of riding skill and style of cyclists, psychometric analysis of the CSI was conducted using a large international sample size (**Chapter 6**). The results indicated that two components underlie the data: motor-tactical skills and safety motives. These results are similar to results obtained among car drivers using the Driving Skill Inventory. It was further found that cyclists who reported a higher number of accidents during the last three years had a lower safety-motives score. The study also confirmed the existence of gender differences found earlier among car drivers: male cyclists had lower safety motives but higher motor-tactical skills than female cyclists.

In **Chapter 7**, a PC-based hazard anticipation training for adult cyclists was developed and evaluated among electric bicycle users. This was a training that uses video-clips of hazardous situations taken from a cyclist perspective. The training was designed based on evidence-based educational methods such as a 'what happens next?' questions, expert commentary, performance feedback, and 'analogical transfer' between hazardous situations. A short-term evaluation of the training indicated that experienced cyclists' hazard anticipation skills improved due to the developed training (i.e., a reduced time to identify novel hazards) as compared to a control group. However, no significant difference was observed in the perceived risk in hazardous situations.

In conclusion, this dissertation contributed to the understanding of two-wheeler users' factors at the tactical and operational levels during interactions with cars and in low-speed tasks for which stabilization skills are needed. The results from the empirical studies described in this thesis can be applied to the development of road safety measures concerning 1) engineering (e.g., vehicle-to-vehicle communication technology, rear-view assistant technology, adjustments in road design), 2) education (e.g., hazard anticipation training, strategies that promote forgiveness), and 3) enforcement (e.g., speed cameras on bike paths, two independently working hand brakes, visibility of two-wheeler users).

SAMENVATTING

Tweewielige voertuigen (fietsen, bromfietsen, motoren) worden steeds populairder in drukke steden vanwege hun kleine dimensies, lage kosten vergeleken met auto's en hun bijdrage aan een gezonde leefstijl. Ook al zitten er voordelen aan het gebruik van tweewielige voertuigen, hun slechte zichtbaarheid, instabiliteit, en de kwetsbaarheid van de gebruikers zorgen voor veiligheidsrisico's. Omdat ze relatief klein zijn worden tweewielige voertuigen gemakkelijk over het hoofd gezien door andere weggebruikers, vooral nabij kruisingen. Bovendien wordt de stabiliteit van tweewielige voertuigen gemakkelijk beïnvloed door verstoringen zoals een oneffen wegdek. Verder zorgt de onbeschermd toestand van de gebruikers van tweewielige voertuigen voor een verhoogd risico op ernstige verwondingen in het geval van een aanrijding.

Het onderzoek in dit proefschrift richt zich op de cognitieve en motorische prestaties van de gebruikers van tweewielige voertuigen in veiligheidskritische situaties. Experimenten zijn uitgevoerd met reguliere fietsers, gebruikers van elektrische fietsen, en gebruikers van motorfietsen. Een elektrische fiets is een relatief nieuw type voertuig dat vooral gebruikt wordt door oudere mensen. Deze trend zorgt voor een extra veiligheidsrisico omdat ouderen een zwakke groep zijn in het verkeer vanwege hun fysieke fragiliteit.

De eerste focus van dit proefschrift betreft onderzoek naar de gevaarherkenningsprestaties van fietsers en of deze gevaarherkenningsprestaties verbeterd kunnen worden middels een korte trainingsinterventie. De volgende twee onderzoeksvragen worden geadresseerd:

- 1) Welke situatie- en persoonsgebonden factoren beïnvloeden de gevaarherkenningsprestaties van fietsers in gevaarlijke situaties op kruisingen?
- 2) Hoe beïnvloedt een trainingsinterventie de gevaarherkenningsprestaties en de risicoperceptie van fietsers?

De tweede focus van dit proefschrift betreft onderzoek naar de stuurprestaties van gebruikers van tweewielige voertuigen tijdens kritische situaties nabij kruisingen en tijdens het uitvoeren van taken op lage snelheid. De volgende twee onderzoeksvragen worden geadresseerd:

- 3) Hoe zijn kenmerken van gebruikers van tweewielige voertuigen op het strategische en tactische niveau geassocieerd met remprestaties in veiligheidskritische situaties voor kruisingen?
- 4) Hoe verschillen de fietsprestaties tijdens lage-snelheidstaken tussen het rijden op een elektrische fiets en het rijden op een conventionele fiets?

In Hoofdstuk 2–4 zijn de gevaarherkenningsvaardigheden en remprestaties van gebruikers van tweewielige voertuigen in veiligheidskritische situaties op kruisingen onderzocht. Allereerst, werden in **Hoofdstuk 2** de oogbewegingen en oversteekbeslissingen van fietsers op gelijkwaardige vierwegskruisingen onderzocht middels van geanimeerde videoclips. The eye-tracking resultaten lieten zien dat de fietsers keken naar de naderende auto wanneer deze auto relevant was voor de

beslissingstaak en wanneer deze auto een gevaar vormde; de fietsers hadden vrijwel geen aandacht voor de naderende auto nadat deze was stopt of de kruising was gepasseerd. Het effect van fietssnelheid (15, 25, of 35 km/u) op oogbewegingen en oversteekbeslissingen was slechts klein. Deze studie liet zien hoe de oogbewegingen en oversteekbeslissingen van fietsers worden beïnvloed door situatiegerelateerde factoren, maar welke visuele signalen de gevaarherkennings- en remprestaties beïnvloeden moest nog worden onderzocht.

Een video-gebaseerde vragenlijst in **Hoofdstuk 3** had als doel te begrijpen welke visuele signalen voor fietsers een bijdrage leveren aan correcte en incorrecte voorspellingen van voorrangsovertredingen van autobestuurders, en welke factoren voorspellend zijn voor of de fietser aangeeft af te zullen remmen. De resultaten lieten zien dat de voorspelling van de fietser wat betreft de actie van de autobestuurder zich ontwikkelden met de tijd: de voorspellingen waren het nauwkeurigst wanneer de tijd tot het conflict het kleinst was. Zowel 'bottom-up' (bv. de snelheid van de auto) en 'top-down' signalen (bv. verkeersregels en eerdere ervaringen) bleken de voorspellingen van wat de autobestuurder ging doen te beïnvloeden. Fietsers die aangaven dat de snelheid van de auto hoog was of dat de auto aan het versnellen was gaven vaker correct aan dat de auto de fietser niet als eerste de kruising liet oversteken. Daarentegen, fietsers die aangaven dat de snelheid van de auto laag was, dat de auto aan het afremmen was, of dat de fietser voorrang had waren meer geneigd foutief te geloven dat de auto voorrang zou verlenen aan de fietser. Correcte voorspellingen van de voorrangsovertreding van de autobestuurder en een hoge risicoperceptie waren geassocieerd met zelfgerapporteerd afremmen.

Na de gevaarherkenningsvaardigheden te hebben bestudeerd moest nog onderzocht worden of gebruikers van tweewielers in staat zijn om een remmanoeuvre op zo'n manier uit te voeren dat een ongeluk voorkomen wordt als een autobestuurder geen voorrang geeft. Hiertoe is een studie in een motorfietssimulator opgezet (**Hoofdstuk 4**) met het doel te onderzoeken hoe bestuurders van een motorfiets remmen in botsing, bijna-botsing, en veilige situaties op kruisingen. De naderingsrichting van de auto (komend vanuit de tegengestelde richting vs. komend van rechts), de beweging van de auto (rechtdoor rijden, een linkerbocht inzetten en dan stoppen, of linksaf slaan), en het gebruik van de richtingaanwijzers (aan vs. uit) werden gemanipuleerd. De resultaten lieten zien dat, hoewel de bestuurders van de motorfiets remden in het overgrote deel van de gevallen waar de auto hun pad kruiste, ze vaak niet in staat waren om een botsing met de auto te vermijden. De conclusie die opdoemt uit deze studies is dat, als een autobestuurder de voorrangsregels op een kruising overtreedt, het wellicht onmogelijk is voor de gebruiker van de tweewieler om een botsing te voorkomen.

Ongevalstatistieken geven aan dat gebruikers van elektrische fietsen vaker betrokken zijn bij enkelvoudige fietsongevallen dan gebruikers van conventionele fietsen; dit suggereert dat gebruikers van elektrische fietsen moeite hebben met het uitvoeren van manoeuvreertaken. In **Hoofdstuk 5** worden de stuurprestaties op een conventionele fiets en een elektrische fiets onderzocht onder fietsers van middelbare en oudere leeftijd voor

drie lagesnelheidstaken waarvoor stabilisatievaardigheden van belang zijn. De lagesnelheidstaken waren: langzaam fietsen met ongeveer 7 km/u, versnellen tot een snelheid van 17 km/h, en een schoudercontrole waarbij de fietser gevraagd was om richting aan te geven met de linkerhand en tegelijkertijd over de linkerschouder te kijken. De resultaten lieten zien dat tijdens fietsen op lage snelheid en tijdens de schoudercontrole, de oudere fietsers meer stuurinput gaven en een grotere rolbeweging van de fiets vertoonden vergeleken met de fietsers van middelbare leeftijd. Dus, ook al bieden elektrische fietsen voordelen voor ouderen, ouderen ervaren moeilijkheden op het operationele niveau en hebben daarom mogelijk baat bij nieuwe technologieën die ze bepaalde taken helpen uitvoeren. Elektrische fietsen stelden de fietsers in staat sneller te accelereren naar een kruissnelheid vergeleken met conventionele fietsen.

In Hoofdstuk 5 vulden deelnemers een 'Cycling Skill Inventory' (CSI) in, een vragenlijst die subjectieve fietsvaardigheden vastlegt. De resultaten lieten slechts kleine correlaties zien tussen de zelf-beoordeelde fietsprestaties en hun daadwerkelijke prestaties tijdens de lagesnelheidstaken. Deze kleine correlaties kunnen worden verklaard door het feit dat de CSI een variëteit aan vaardigheden navraagt terwijl het experiment zich enkel richtte op motorische vaardigheden. Omdat slechts weinig kennis bestond over de zelfbeoordeling van fietsvaardigheid en fietsstijl onder fietsers was een psychometrische analyse van de CSI uitgevoerd gebruik makend van een grote internationale sample (**Hoofdstuk 6**). De resultaten lieten zien dat er twee componenten onderliggend zijn aan de data: motorische-tactische vaardigheden en veiligheidsmotieven. Deze resultaten zijn gelijkwaardig aan resultaten die verkregen zijn onder autobestuurders met behulp van de Driving Skill Inventory. Verder werd gevonden dat fietsers die veel ongelukken in de laatste drie jaar rapporteerden een lage veiligheidsmotieven-score hadden. Deze studie bevestigt ook de aanwezigheid van man-vrouw verschillen die eerder ook onder autobestuurders zijn gevonden: mannelijke fietsers hadden een lagere veiligheidsmotieven-score maar een hogere motorische-tactische-vaardigheden-score dan vrouwelijke fietsers.

In **Hoofdstuk 7** is een PC-gebaseerde gevaarherkenningstraining voor volwassen fietsers ontwikkeld en geëvalueerd onder gebruikers van elektrische fietsen. Dit was een training die gebruik maakt van video clips van gevaarlijke situaties bekenen vanuit het perspectief van de fietser. De training was ontworpen gebaseerd op evidence-based educatiemethoden, waaronder 'wat gebeurt hierna?' vragen, commentaar van een expert, prestatie feedback, en 'analoge overdracht' tussen gevaarlijke situaties. Een korte-termijn evaluatie van de training liet zien dat de gevaarherkenningsvaardigheden van de ervaren fietsers verbeterde door de ontwikkelde training (d.w.z., een kortere benodigde tijd om gevaren te identificeren) vergeleken met een controlegroep. Echter, er was geen significant verschil geobserveerd wat betreft risicoperceptie in gevaarlijke situaties.

Concluderend, dit proefschrift heeft bijgedragen aan het begrip van de tactische en operationele factoren onder gebruikers van tweewielers tijdens interacties met auto's en tijdens taken op lage snelheid waarvoor stabilisatievaardigheden van belang zijn. De

resultaten van de empirische studies beschreven in dit proefschrift kunnen worden toegepast op de ontwikkeling van verkeersveiligheidsmaatregelen betreffende 1) engineering (bv. voertuig-tot-voertuig communicatietechnologie, technologie betreffende achteruitkijkassistentie, aanpassingen in het wegontwerp), 2) educatie (bv. gevaarherkenningstraining, strategieën die vergevingsgezind gedrag in het verkeer stimuleren, en 3) handhaving (bv. snelheidscamera's op fietspaden, twee onafhankelijk werkende handremmen, en de zichtbaarheid van gebruikers van tweewielige voertuigen).

CHAPTER 1

GENERAL INTRODUCTION

1.1. Two-wheeler vehicles' characteristics and accident rates

Bicycles, mopeds, and motorcycles (also called two-wheelers or single-track vehicles) are efficient modes of transport, especially in congested cities. Their low cost of use compared to cars, their small dimensions, and their contribution to a healthy lifestyle are key factors behind the increased use of these vehicles (Shinar, 2012; Wegman et al., 2012). However, their use differs greatly between countries: from almost non-existing up to everyday use among a large number of inhabitants in the Netherlands and Denmark in the case of bicycles (Wegman et al., 2012) and in China and India in the case of motorcycles (Haworth, 2012).

As can be seen in Table 1.1, two-wheeler vehicles can be divided into three categories based on their technical capabilities: bicycles (conventional bicycles and electric bicycles), category L1e vehicles (speed pedelecs and mopeds), and category L3e vehicles (motorcycles without sidecar). Relatively new types of two-wheelers are bicycles with a pedal-assist electric drive system that provides assistance for pedaling up to 25 km/h (electric bicycle) or up to 45 km/h (speed pedelec). Electric bicycles and speed pedelecs have gained popularity over the last decade and have been adopted, especially by older people and commuters (Fishman & Cherry, 2016; MacArthur et al., 2014).

Table 1.1. The characteristics of two-wheeler vehicle categories (European Parliament and the Council of the European Union, 2006, 2013).

Vehicle	Bicycle	Electric bicycle	Speed pedelec	Moped	Motorcycle	Motorcycle	Motorcycle
Vehicle category	Bicycle	Bicycle	L1e	L1e	L3e	L3e	L3e
Driving license	No	No	AM	AM	A1	A2	A
Maximum design speed	–	≤ 25 km/h	≤ 45 km/h	≤ 45 km/h	–	–	–
Engine (motor) power	–	≤ 0.25 kW	≤ 4 kW	≤ 4 kW	< 11 kW	< 35 kW	unlimited
Engine displacement	–	–	–	< 50 cc	< 125 cc	≥ 125 cc	unlimited

Despite their potential environmental, space-related, and health benefits, drawbacks of two-wheeler vehicles are their instability (Kooijman & Schwab, 2013), low conspicuity (Pai, 2011; Räsänen & Summala, 1998), and vulnerability. Because their two wheels are positioned in line, two-wheelers require effort to keep stability at low speeds, and they are easily affected by disturbances such as an uneven road surface or small objects on the road (Schepers & Wolt, 2012; Van Elslande & Elvik, 2012). These factors contribute to single-vehicle loss of stability accidents. Due to their small size, two-wheelers tend to be overseen by other road users, and their approach speed is easily misestimated (Crundall et al., 2012; Haworth & Debnath, 2013; Schleinitz et al., 2019). The low

conspicuity contributes to multiple-vehicle accidents, especially at intersections where road user interactions are not regulated by infrastructure elements such as traffic lights. Cyclists and motorcyclists are not protected by passive vehicle safety systems and are therefore often referred to as vulnerable road users. In 2018, more than half of road fatalities worldwide were vulnerable road users (two- and three-wheelers and pedestrians) (WHO, 2018). Looking at safety data from European countries (Fig. 1.1), the number of fatalities among car occupants, moped riders, and motorcycle riders has decreased over the last decade, whereas the number of cyclist fatalities has remained relatively stable since 2010 (European Commission, 2018). In the Netherlands, where approximately 30% of trips take place by bicycle (Wegman et al., 2012), the numbers of fatalities among cyclists and car drivers were equal (434 vs. 434 out of 1.291 fatalities among all road users in 2017 and 2018 combined) (CBS Statline, 2019). Overall, safety data points out that the risk of death in traffic (number of traffic fatalities per km traveled) is substantially higher for two-wheeler users compared to car occupants (SWOV, 2019).

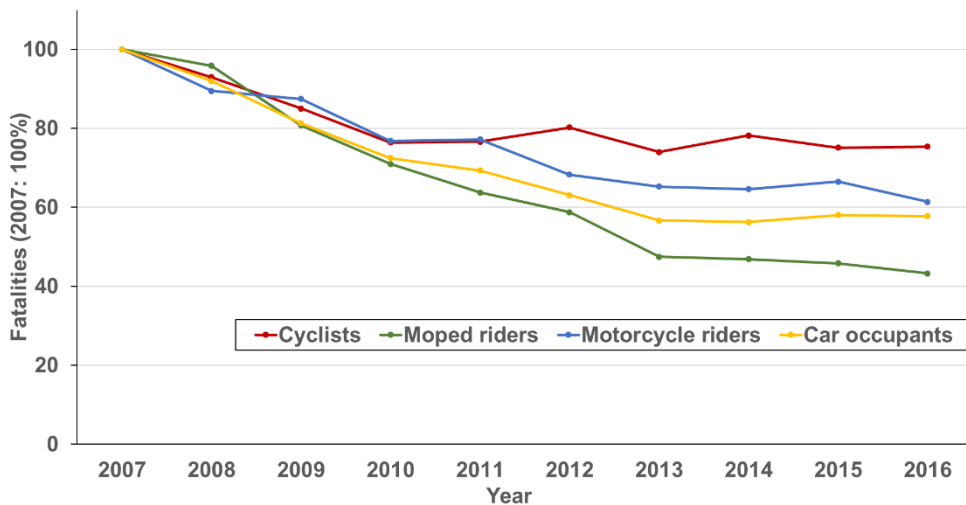


Fig. 1.1. The annual number of fatalities between 2007–2016 by user group in European countries (European Commission, 2018).

Robust accident data is essential for assessing the effectiveness of measures that aim to reduce fatalities and injuries (WHO, 2019). However, current two-wheeler crash data suffer from underreporting, especially when no motor vehicle is involved (Wegman et al., 2012). The incomplete view of accidents is also caused by coding practices and the failure to distinguish between different two-wheeler types, for instance between conventional and electric bicycles (Fishman & Cherry, 2016; Twisk et al., 2013). Thus, it is unknown whether the high level of risk faced by two-wheeler users is attributable to their vulnerability or whether it arises from their errors or risk-taking (Van Elslande & Elvik, 2012). To be able to improve the safety of cyclists and motorcyclists, we should

gain a better understanding of how crashes occur in the rider-vehicle-road system (Hagenzieker et al., 2014).

1.2. Scope of the dissertation

The popularity of two-wheelers creates several safety concerns. A major concern relates to older users, who are considered to be the most vulnerable group in traffic because of their physical frailty (OECD, 2001). Furthermore, it is known that cyclists and motorcyclists experience critical situations at intersections when a car driver fails to yield. However, limited research exists on the understanding of this traffic situation from the two-wheeler's perspective.

The research in this dissertation focuses on the motor and cognitive performance of two-wheeler users in safety-critical situations. Experiments were conducted among conventional cyclists, users of electric bicycles, and motorcycle users. As all two-wheeler users encounter similar safety-critical safety situations at intersections (i.e., right-of-way accidents), the results might apply to all users, but with a certain caution due to vehicle-specific characteristics.

Riding a two-wheeled vehicle can be conceptualized as a hierarchy, with at the higher level the user's behaviors and motivations and at the lower levels the tactical decisions and the task execution. In his hierarchical model of road user behavior, Michon (1985) distinguished three levels; ordered from highest to lowest level these are the strategic (planning), the tactical (maneuvering), and the operational level (control). Similarly, Donges (1982) distinguished between the navigation level, guidance level, and stabilization level. The distinction between higher-level motivation and lower-level control is equivalent to the distinction between violations and errors (Reason et al., 1990; Parker, 2007; De Winter et al., 2015), the distinction between driver behavior and driver performance (Evans, 2004), and the distinction between driving style and driving skill (Elander et al., 1993). Michon's hierarchy was used as a framework for the studies included in this dissertation (see Fig. 1.2).

The focus of the highest level of the task hierarchy (strategic level) is on planning tasks and includes factors such as physical and mental abilities, personality, risk acceptance, and behavioral style (Hatakka et al., 2002; Michon, 1985). Because of their small size and high maneuverability, two-wheelers provide an opportunity for risky behaviors such as filtering, overtaking other road users within the same lane, or doing a wheelie. These behaviors are not encountered among car drivers for whom the road is designed (Van Elslande & Elvik, 2012). Furthermore, two-wheeler users' attitudes towards passive safety equipment such as helmets, protective clothing, or bright strips could influence the severity of injuries once an accident happens. This level is addressed mainly by legislation, enforcement, and educational safety campaigns. Although the strategic level is not the primary focus of this dissertation, we investigated cyclists' perceived risk when interacting with car drivers at interactions, as well as how hazard anticipation training influences perceived risk in hazardous traffic situations.

At the middle level (tactical level), two-wheeler users anticipate and adjust their riding performance in accordance with prevailing circumstances on the road (Hatakka et al., 2002; Michon, 1985). This level refers to hazard anticipation skills, knowledge of traffic rules, and expectations of other road users' actions. 'Knowing what is going on' can be captured by the three-level situational awareness theory of Endsley (1995). Level 1 situation awareness refers to the perception of individual elements of the situation, Level 2 involves the comprehension of their meaning and importance, and at Level 3 a user predicts the future status of the situation. Poor hazard anticipation skill has been associated with crash involvement (Horswill & McKenna, 2004), but limited knowledge exists on hazard anticipation among two-wheeler users. Remedial measures at this level are cooperative applications between road users (e.g., cyclist and car driver) that provide a warning about an approaching road user or support a user in interpreting the other road users' actions. Obtaining an understanding of users' hazard anticipation performance in critical situations is essential for the development of these technologies as well as for designing training curricula.

The first scope of this dissertation is to investigate cyclists' hazard anticipation performance in hazardous situations and to examine whether hazard anticipation can be enhanced with a short training intervention.

- 1) Which situational and individual factors influence cyclists' hazard anticipation performance in safety-critical situations at intersections?
- 2) How does a training intervention affect cyclists' hazard anticipation performance and perceived risk?

The lowest level of the hierarchy (operational level) refers to vehicle control and handling skills (Michon, 1985). These motor skills are developed at the very beginning when a user starts to interact with a vehicle, and are traditionally treated in training programs. Relevant technologies at this level are active safety systems such as autonomous emergency braking or curve assist systems that support the user during the riding task (Savino et al., 2019). Active safety systems, however, exist only for powered two-wheelers (mopeds, motorcycles) and have not been developed for bicycles.

The second scope of this dissertation is to investigate users' riding performance and their self-assessments in critical intersection situations and in low-speed tasks.

- 3) How are two-wheeler users' characteristics at the strategic and tactical levels associated with braking performance in safety-critical intersection situations?
- 4) How does cycling performance in low-speed tasks differ between riding an electric bicycle and riding a conventional bicycle?

As mentioned above, the understanding of user actions in traffic situations is essential for the design and development of effective safety measures. Road safety measures are traditionally categorized into the three 'Es': Education, Engineering, and Enforcement (Learoyd, 1950; Rothengatter, 1982; McKenna, 2012). Education intends to improve the skills, knowledge, and behavior of users. In this dissertation, education is addressed by

designing a hazard anticipation training program. Engineering refers to the invention, design, construction, and modification of physical, digital, haptic, and voice systems. Examples are vehicles, personal protective equipment, road design, as well as future internet technologies related to communication and big data. The results of this dissertation may be used as a base for designing future cooperative technologies between drivers and (motor) cyclists at intersections. Lastly, enforcement includes the development and application of laws and regulations that aim to eliminate undesired user behaviors and set vehicle safety standards. As part of the tactical level, users' traffic rules knowledge was investigated in this dissertation.

1.3. Dissertation outline

This dissertation consists of three primary empirical studies (*Chapters 2–4*), two evaluation studies (*Chapters 5 and 7*), and one methodological study (*Chapter 6*). The structure of these research studies is depicted in Fig. 1.2. The results of the studies are summarized, and the implications are discussed in *Chapter 8*.

Chapters 2, 3, and 4 contain key empirical studies into two-wheelers' anticipation of car drivers' right-of-way violations at intersections, emergency responses, and perceived risk. A mixed-method design (termed triangulation; Jick, 1979) was used: participants' perception and emergency braking behavior were measured using an eye-tracker, self-reports, a spacebar pressing task, and an interactive motion-based motorcycle simulator. The research reported in Chapters 2 and 3 was conducted among cyclists, and the research reported in Chapter 4 among motorcyclists. Due to safety concerns, these studies were conducted in a laboratory and via remote Internet data collection. These studies targeted individuals' factors across all three levels of the riding task hierarchy (Michon, 1985).

Chapters 5 and 6 focus on cyclists' performance measured by instrumented bicycles and self-reports. Riding performance on a conventional and electric bicycle of middle-aged and older cyclists was compared in three low-speed exercises for which stabilization skills are important. This was a between- and within-subject field operational experiment. In addition to the objective evaluation of cyclists' performance using two types of bicycles, self-ratings of their motor-tactical and safe cycling skills were assessed. In Chapter 6, a psychometric analysis of this self-assessment tool (Cycling Skill Inventory) was conducted using a cross-national sample of cyclists. These studies targeted individuals' factors primary at the lowest level of the riding task hierarchy (Michon, 1985), although the Cycling Skill Inventory also includes items at the other two levels of the hierarchy.

Chapter 7 describes the design of the PC-based hazard anticipation training for experienced adult cyclists and its evaluation. This hazard anticipation training consists of video-clips of hazardous traffic situations taken from a cyclist perspective and was designed using various evidence-based educational methods such as a 'what happens next?' task, expert commentary, performance feedback, and analogical transfer between hazardous situations. A short-term evaluation of the training was conducted among

electric bicycle users in a laboratory setting. This study targeted safety measures at the tactical level (Michon, 1985).

Lastly, the main findings, their implications to the education and engineering fields, and the remaining knowledge gaps are discussed in *Chapter 8*.

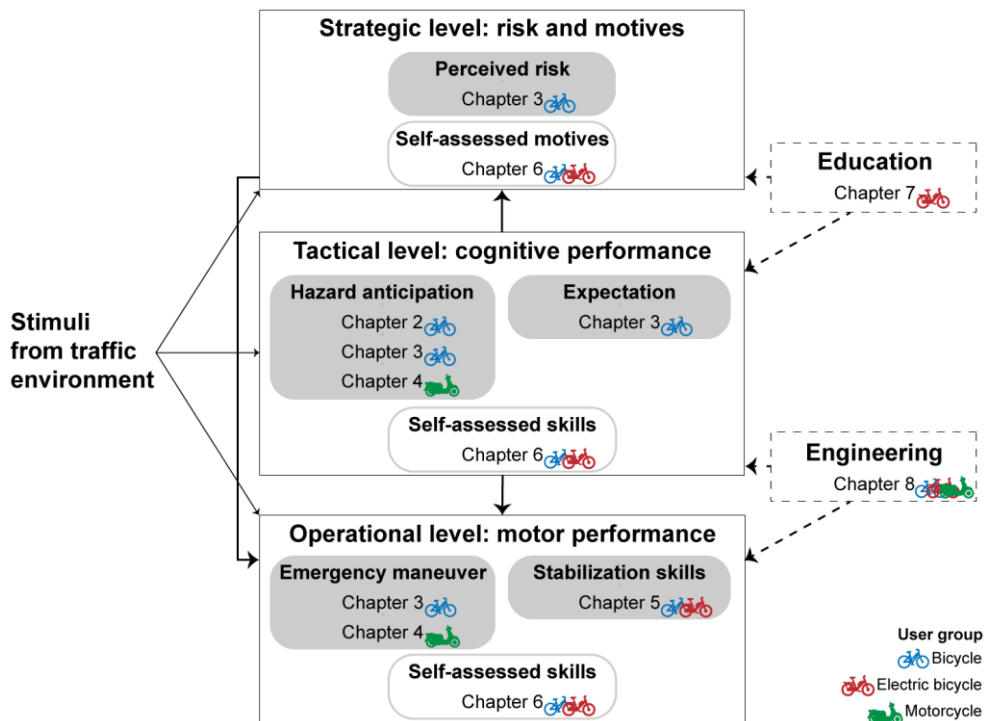


Fig. 1.2. The structure of this dissertation based on Michon's riding task hierarchy (1985). The vehicle icon indicates the user group participating in the particular study. The solid lines indicate the studied relationships in this dissertation. The dashed lines indicate Education and Engineering recommendations. Note that Chapters 2–7 are research studies, and Chapter 8 provides a discussion.

References

- CBS Statline (2019). *Overledenen; doden door verkeersongeval in Nederland, wijze van deelname* [Road fatalities in the Netherlands by road user group].
- Crundall, D., Crundall, E., Clarke, D., & Shahar, A. (2012). Why do car drivers fail to give way to motorcycles at t-junctions? *Accident Analysis & Prevention*, *44*, 88–96.
- De Winter, J. C., Dodou, D., & Stanton, N. A. (2015). A quarter of a century of the DBQ: Some supplementary notes on its validity with regard to accidents. *Ergonomics*, *58*, 1745–1769.

- Donges, E. (1982). Aspekte der Aktiven Sicherheit bei der Führung von Personenkraftwagen [Aspects of active safety when operating cars]. *Automobil-Industrie*, 27, 183–190.
- Elander, J., West, R., & French, D. (1993). Behavioral correlates of individual differences in road-traffic crash risk: An examination of methods and findings. *Psychological Bulletin*, 113, 279–294.
- Endsley, M. R. (1995). Toward a theory of situational awareness in dynamic systems. *Human Factors*, 37, 32–64.
- European Commission (2018). *Annual Accident Report 2018*. European Commission: Directorate General for Transport.
- European Parliament and the Council of the European Union (2006). *Directive 2006/126/EC on driving licences*, 20th December 2006. Retrieved from <http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex:32006L0126>.
- European Parliament and the Council of the European Union (2013). *Regulation (EU) No 168/2013 of the European Parliament and of the Council of 15 January 2013 on the approval and market surveillance of two- or three-wheel vehicles and quadricycles*, 2nd March 2013. Retrieved from <https://eur-lex.europa.eu/legal-content/en/TXT/?uri=CELEX:32013R0168>.
- Evans, L. (2004). *Traffic safety*. Bloomfield Hills, MI: Science Serving Society.
- Fishman, E., & Cherry, C. (2016). E-bikes in the Mainstream: Reviewing a Decade of Research. *Transport Reviews*, 36, 72–91.
- Hagenzieker, M. P., Commandeur, J. J., & Bijleveld, F. D. (2014). The history of road safety research: A quantitative approach. *Transportation Research Part F: Traffic Psychology and Behaviour*, 25, 150–162.
- Hatakka, M., Keskinen, E., Gregersen, N. P., Glad, A., & Hernetkoski, K. (2002). From control of the vehicle to personal self-control; broadening the perspectives to driver education. *Transportation Research Part F: Traffic Psychology and Behaviour*, 5, 201–215.
- Haworth, N. (2012). Powered two wheelers in a changing world—Challenges and opportunities. *Accident Analysis & Prevention*, 44, 12–18.
- Haworth, N., & Debnath, A. K. (2013). How similar are two-unit bicycle and motorcycle crashes? *Accident Analysis & Prevention*, 58, 15–25.
- Horswill, M. S., & McKenna, F. P. (2004). Drivers' hazard perception ability: Situation awareness on the road. In S. Banbury and S. Tremblay (Eds.), *A cognitive approach to situation awareness: Theory and application* (pp. 155–175) UK: Ashgate Publishing, Ltd.
- Jick, T. D. (1979). Mixing qualitative and quantitative methods: Triangulation in action. *Administrative Science Quarterly*, 24, 602–611.
- Kooijman, J. D. G., & Schwab, A. L. (2013). A review on bicycle and motorcycle rider control with a perspective on handling qualities. *Vehicle System Dynamics*, 51, 1722–1764.
- Learoyd, C. G. (1950). The carnage on the roads. *The Lancet*, 255, 367–369.

- MacArthur, J., Dill, J., & Person, M. (2014). Electric bikes in North America: Results of an online survey. *Transportation Research Record*, 2468, 123–130.
- McKenna, F. P. (2012). How should we think about the three E's: education, engineering and enforcement? In the *5th International Conference on Traffic and Transport Psychology*, Groningen, the Netherlands, August 29–31, 2012.
- Michon, J. A. (1985). A critical view of driver behavior models: What do we know, what should we do? In L. Evans & R. C. Schwing (Eds.), *Human behavior and traffic safety* (pp. 485–524). New York: Plenum Press.
- OECD (2001). *Ageing and transport: Mobility needs and safety issues*. Paris: OECD Publishing.
- Pai, C. W. (2011). Motorcycle right-of-way accidents—A literature review. *Accident Analysis & Prevention*, 43, 971–982.
- Parker, D. (2007). Driver error and crashes. In P.C. Cacciabue (Ed.), *Modelling driver behaviour in automotive environments: Critical issues in driver interactions with intelligent transport systems* (pp. 266–274). London: Springer-Verlag.
- Räsänen, M., & Summala, H. (1998). Attention and expectation problems in bicycle–car collisions: an in-depth study. *Accident Analysis & Prevention*, 30, 657–666.
- Reason, J., Manstead, A., Stradling, S., Baxter, J., & Campbell, K. (1990). Errors and violations on the roads: A real distinction? *Ergonomics*, 33, 1315–1332.
- Rothengatter, T. (1982). The effects of police surveillance and law enforcement on driver behaviour. *Current Psychological Reviews*, 2, 349–358.
- Savino, G., Pierini, M., & Fitzharris, M. (2019). Motorcycle active safety systems: Assessment of the function and applicability using a population-based crash data set. *Traffic Injury Prevention*, 20, 406–412.
- Schepers, P., & Wolt, K. K. (2012). Single-bicycle crash types and characteristics. *Cycling Research International*, 2, 119–135.
- Schleinitz, K., Petzoldt, T., & Gehlert, T. (2019). Drivers' gap acceptance and time to arrival judgements when confronted with approaching bicycles, e-bikes, and scooters. *Journal of Transportation Safety & Security*, 1–14.
- Shinar, D. (2012). Safety and mobility of vulnerable road users: Pedestrians, bicyclists, and motorcyclists. *Accident Analysis & Prevention*, 44, 1–2.
- SWOV (2019). *Verkeersdoden in Nederland* [Road fatalities in the Netherlands]. SWOV Factsheet. SWOV Institute for Road Safety Research: The Hague.
- Twisk, D., Vlakveld, W., Dijkstra, A., Reurings, M., & Wijnen, W. (2013). *From bicycle crashes to measures*. Leidschendam: SWOV Institute for Road Safety Research.
- Van Elslande, P., & Elvik, R. (2012). Powered two-wheelers within the traffic system. *Accident Analysis & Prevention*, 49, 1–4.
- Wegman, F., Zhang, F., & Dijkstra, A. (2012). How to make more cycling good for road safety? *Accident Analysis & Prevention*, 44, 19–29.
- WHO World Health Organization (2018). *Global status report on road safety 2018*. Geneva: World Health Organization.

CHAPTER 2

CYCLISTS' EYE MOVEMENTS AND CROSSING JUDGMENTS AT UNCONTROLLED INTERSECTIONS: AN EYE-TRACKING STUDY USING ANIMATED VIDEO CLIPS

Research indicates that crashes between a cyclist and a car often occur even when the cyclist must have seen the approaching car, suggesting the importance of hazard anticipation skills. This study aimed to analyze cyclists' eye movements and crossing judgments while approaching an intersection at different speeds. Thirty-six participants watched animated video clips with a car approaching an uncontrolled four-way intersection and continuously indicated whether they would cross the intersection first. We varied (1) car approach scenario (passing, colliding, stopping), (2) traffic complexity (one or two approaching cars), and (3) cyclist's approach speed (15, 25, or 35 km/h). Results showed that participants looked at the approaching car when it was relevant to the task of crossing the intersection and posed an imminent hazard, and they directed less attention to the car after it had stopped or passed the intersection. Traffic complexity resulted in divided attention between the two cars, but participants retained most visual attention to the car that came from the right and had right of way. Effects of cycling speed on cyclists' gaze behavior and crossing judgments were small to moderate. In conclusion, cyclists' visual focus and crossing judgments are governed by situational factors (i.e., objects with priority and future collision potential), whereas cycling speed does not have substantial effects on eye movements and crossing judgments.

Kovácsová, N., Cabral, C. D. D., Antonisse, S. J., de Haan, T., van Namen, R., Nooren, J. L., Schreurs, R., Hagenzieker, M. P., & De Winter, J. C. F. (2018). Cyclists' eye movements and crossing judgments at uncontrolled intersections: An eye-tracking study using animated video clips. *Accident Analysis & Prevention*, 120, 270–280.

2.1. Introduction

Naturalistic cycling studies and accident data analyses indicate that cyclists are particularly at risk when encountering a car at an intersection (Akhtar et al., 2010; Dozza et al., 2016; Schepers et al., 2011; Summala et al., 1996). Contributory factors to bicycle-car collisions at intersections include the driver's failure in perceiving the cyclist and the cyclist's incorrect anticipation of the driver's intentions (Räsänen & Summala, 1998). Similarly, analyses of car-car and motorcycle-car intersection crashes have found that not only perceptual errors, but also false assumptions about the other's future actions are frequent causes of crashes (Choi, 2010; Najm et al., 1994; Pai, 2011).

The importance of 'knowing what is going on' in the environment can be captured by the construct of situation awareness, comprising three levels (Endsley, 1995). Level 1 is the perception of individual elements of the scene, Level 2 involves the comprehension of their meaning and importance, and at Level 3 the road user anticipates future events, such as a car driver's intentions. Researchers have identified several factors that are associated with perceptual errors at intersections, such as information processing limitations and perceptual filtering (e.g., Crundall et al., 2008; Herslund & Jørgensen, 2003; Scott et al., 2013; Werneke & Vollrath, 2012). However, less empirical evidence exists concerning the mechanisms responsible for road users' failures in comprehension and anticipation of other road users' intentions.

Several studies have used time-to-arrival judgments tasks to examine participants' anticipation of the future location of other road users (e.g., Caird & Hancock, 1994; Hancock & Manster, 1997; Van Loon et al., 2010), gap acceptance or interception tasks to investigate under which conditions individuals cross an intersection (e.g., Chihak et al., 2010; Grechkin et al., 2013; Lobjois et al., 2013; Louveton et al., 2012; Simpson et al., 2003), and judgment tasks to examine the perceived risk associated with crossing the intersection in front of an approaching car (e.g., Ebbesen et al., 1977). Stimuli for these tasks included cars approaching intersections at constant speeds while the participant was either stationary or moving toward the intersection. Chihak et al. (2010) used a bicycle simulator to investigate how children and adult cyclists adjust their approach speed to successfully pass through a gap in crossing traffic. Their results indicated that instead of cycling at a constant speed, cyclists used a two-stage interception strategy where they slowed down first, and accelerated when being close to the intersection (approximately 4–6 s). A possible reason why cyclists adjust their approach speed is that it allows them to improve the timing of the entry into the gap while minimizing the amount of time spent in the path of the oncoming traffic. Traditionally, the emphasis has been on how accurately people make judgments about potential collisions and on the probability/timing of crossing the intersection, whereas relatively little attention has been paid to what sources of visual information humans use in such tasks.

Early work on fixation allocation using pictures has indicated that viewers do not look randomly at the scene but gaze predominantly to informative areas of the picture (Buswell, 1935; Mackworth & Morandi, 1967). In a traffic environment, informative areas are those where hazards can arise from as well as objects in the visual field relevant to

the performed task (e.g., a vehicle having priority). In an eye-tracking experiment by Van Loon et al. (2010), observers watched animated video clips while making relative timing judgments about approaching vehicles at a T-junction. Results showed that drivers made saccadic movements between the road ahead and the approaching car while spending the most viewing time (37%) on the approaching car. Eye-tracking studies conducted among car drivers have shown that hazardous events reduce saccadic activity (i.e., reduced spread of search) and increase fixation durations on the hazardous object, which may reflect in-depth information processing (Crundall et al., 1999, 2002; Chapman & Underwood, 1998; Velichkovsky et al., 2002). Perceptual narrowing in traffic may be similar to the 'weapon focus' phenomenon whereby observers fixate more often and for a longer duration on a threatening object than on a neutral object (Loftus et al., 1987; Underwood et al., 2003). At intersections, it can be expected that road users shift their attention between potentially hazardous objects while allocating most visual attention to high-value information sources (Werneke & Vollrath, 2012; Wickens et al., 2001).

Humans have evolved to perform ambulatory tasks up to 10 km/h, whereas driving and cycling occur at considerably higher speeds, posing challenges for safety and human information processing (Rumar, 1985). Driving simulator studies have shown that drivers reduce their horizontal gaze variance as driving speed increases (Rogers et al., 2005; Van Leeuwen et al., 2015). When driving at a low speed, road users have more time for perceptual and cognitive processing, whereas at higher speeds they look farther ahead and become more selective in their attention allocation (Summala & Räsänen, 2000).

Formal traffic rules (e.g., the right-hand rule) help road users act in a safe manner (Åberg, 1998). However, road users' behavior is not only governed by formal traffic rules (Özkan & Lajunen, 2005). For example, a driver may let a cyclist cross first, even when the driver has right of way. One explanation for bicycle-car collisions when a cyclist must have seen the car is that the cyclist anticipates that the driver will yield if slowing down, while in fact, that driver is preparing to make a turn and has not seen the cyclist (Summala & Räsänen, 2000). Thus, it is important that cyclists detect relevant information that can be used for confirming or updating preliminary decisions (Näätänen & Summala, 1974).

In the present study, participants were asked to watch animated video clips from the viewpoint of a cyclist. In these video clips, the cyclist encountered different types of car approach scenarios while cycling towards an uncontrolled four-way intersection. We recorded participants' eye movements while participants were tasked to indicate continuously whether they believed they or the car(s) would cross the intersection first, by respectively pressing or releasing the spacebar. The aim of this paper is to investigate how cyclist's eye movements and 'I will cross the intersection first' judgments differ as a function of car approach scenario (passing, collision, stopping), traffic complexity (one vs. two approaching cars), and cycling speed (15, 25, or 35 km/h). The questions addressed in this study are as follows:

1. *How do cyclists' eye movements and their crossing judgments differ between car approach scenarios at the same four-way intersection?*

Based on previous research (e.g., Chapman & Underwood, 1998; Loftus et al., 1987), we hypothesized that when approaching the intersection, participants focus on a car if the car is relevant to their task of crossing the intersection, while gazing less to the car if it is irrelevant and does not pose an imminent hazard. Further, we expected that crossing judgment continuously changes while approaching an intersection based on traffic rules (i.e., the initial appearance of the car) and visual information (i.e., particular approach scenario). To address this research question, three approach scenarios with one car were created: (a) a car coming from the right and passing in front of the cyclist, (b) impending collision with a car coming from the right, (c) a car coming from the right and stopping.

2. How do cyclists' eye movements and their crossing judgments change when traffic complexity increases?

Based on Werneke and Vollrath (2012) and Wickens et al. (2001), we hypothesized that if traffic complexity increases (i.e., more cars approach the intersection), participants divide their attention between the cars relevant to their task. To investigate this research question, a scenario with two cars was added: a car coming from the right and stopping (same as in approach scenario c) together with a car coming from the left that is also stopping. We hypothesized that crossing judgment is done based on the car that has higher task relevance (in this case the car from the right) and, thus, there will be no difference in crossing judgments between scenarios with one or two cars.

3. How do cyclists' eye movements and their crossing judgments differ between three cycling speeds?

We expected visual tunneling whereby cyclists are more likely to glance at the task-relevant sources of information (i.e., an approaching car) if the cycling speed is higher (Summala & Räsänen, 2000; Rogers et al., 2005; Van Leeuwen et al., 2015). Cycling speeds (15, 25, and 35 km/h) were chosen based on previous experiments showing that conventional, electric, and racing bicycles users differ in their speed choice (Hendriksen et al., 2008; Methorst et al., 2011; Schleinitz et al., 2017).

2.2. Methods

2.2.1. Participants

Thirty-seven cyclists (6 females, 31 males) recruited from the Delft University of Technology took part in this study. The age range was 18–27 years (mean = 21.0, $SD = 2.0$). All participants reported normal or corrected-to-normal vision. Thirty-four participants possessed a driving license (mean = 3.0 years; $SD = 1.6$). The participants had started cycling at the age of 3–6 years and 32 of them cycled frequently (i.e., at least 3 days per week). The research was approved by the Human Research Ethics Committee of the Delft University of Technology (Ethics application no. 34, 2016), and all participants provided written informed consent. Participants were financially compensated for their time.

2.2.2. Apparatus

Participants sat approximately 95 cm in front of a 24-inch monitor and rested their head on an adjustable head support. The horizontal field of view (i.e., the size of the screen from the participant's perspective) was approximately 31 degrees. The eye tracker was placed at 60 cm in front of the participants with the lens centered at the right eye. Viewing was binocular, but only the right eye movements were tracked, at a sampling rate of 2000 Hz using the EyeLink 1000 Plus Eye Tracker (SR Research, Canada). Participants used a keyboard to provide input about whether or not they would cross the intersection first. No sounds were provided during the experiment.

2.2.3. Stimuli

Non-interactive animated video clips were designed, in which a cyclist approached an uncontrolled four-way intersection with 4m wide two-lane roads in a suburban environment. A car approached the intersection from the right (CarR) or the left (CarL) (Fig. 2.1). Two more cars were added to the traffic environment in each scenario. One car (CarF) started 40m in front of the bicycle and drove 20 km/h faster than the cyclist. This car drove away from the cyclist and passed the intersection before CarR and CarL arrived at the intersection. The other car (CarT) drove at a relative velocity of 55 km/h towards the cyclist and did not arrive at the intersection before the video ended.

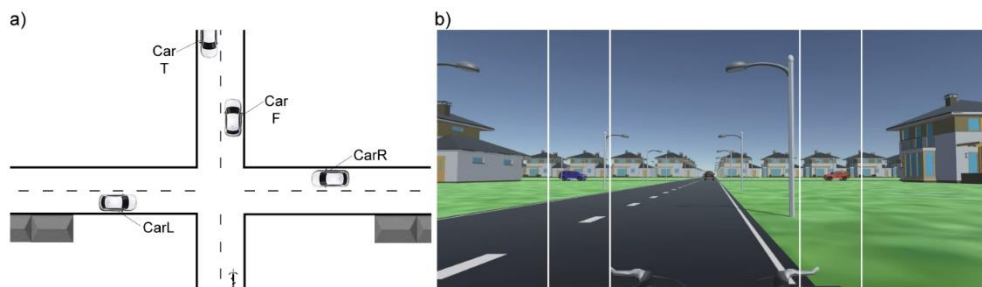


Fig. 2.1. A four-way uncontrolled intersection shown in the video clips: (a) Schematic top-view of the intersection; (b) Screenshot of scenario R&L stop at 25 km/h. The white vertical lines indicate the areas of interest of CarL and CarR.

There were no priority signs and no stop lines, meaning that a vehicle approaching from the right had right of way. The roads were perpendicular to each other, and along each road, there were street lamps.

The cyclist always started at a distance of 100m in front of the intersection. All videos ended when the cyclist was about 5m in front of the intersection. Accordingly, the cyclist never crossed the intersection or collided with a car.

Buildings were positioned approximately 30m from the road (Fig. 2.1). Participants watched the animated video clips from a first-person perspective. A handlebar was

shown at the bottom of the screen to create an impression of cycling. The stimulus materials were built in Unity, a gaming engine. Videos had a frame rate of 30 fps and a resolution of 1920×908 pixels.

Three independent variables were manipulated:

- 1) *Car approach scenario*. The car's motion was manipulated to create three car approach scenarios:
 - a) *R passes*. A car came from the right and slowed down. It crossed the intersection while driving at 20 km/h in front of the cyclist.
 - b) *R collision*. A car came from the right, slowed down to 10 km/h, and continued driving at that speed. It entered the intersection while driving at 10 km/h so that it was on a collision course with the cyclist.
 - c) *R stops*. A car came from the right and stopped in front of the intersection.
- 2) *Traffic complexity*. The traffic complexity was manipulated by the number of approaching cars.
 - a) *R stops*. Only one car approached the intersection and stopped in front of the intersection.
 - b) *R&L stop*. In the 'R stops' scenario, a car from the left was added. Thus, a car came from the right and another car came from the left. Both cars stopped in front of the intersection (see Fig. 2.1 for a screenshot) but CarL stopped approximately 1.5 s earlier than CarR.

Thus, four different intersection scenarios were used in the present experiment: three with one approaching car (i.e., CarR) and one scenario with two approaching cars (i.e., CarR and CarL).

- 3) *Cycling speed*. The participant could approach the intersection at three different speeds. These speeds were combined with the four intersection scenarios, yielding 12 conditions (i.e., video clips). The three levels of cycling speed variable were:
 - a) *15 km/h* (video duration of 22.67 s; CarR appeared in view between 12.87 s and 12.93 s after the start of the video),
 - b) *25 km/h* (13.50 s; CarR appeared in view between 3.60 s and 3.77 s after the start of the video),
 - c) *35 km/h* (9.70 s; CarR appeared in view between 1.13 s and 1.20 s after the start of the video).

To make sure that the desired scenario occurred at all three cycling speeds, the start of CarR and CarL was triggered when the cyclist was at a certain distance to the intersection. This trigger distance was 60, 100, and 100 m, and the starting distance of CarR and CarL to the intersection was 80, 80, and 50 m, for cycling speeds 15, 25, and 35 km/h, respectively. Both cars were triggered at an initial speed of 40 km/h and decelerated to 20 km/h in 'R passes' (deceleration rate was 2.31 m/s²), 10 km/h in 'R collision' (2.89 m/s²), and to 0 km/h in 'R stops' (1.37 m/s²) and in 'R&L stop' (1.37 m/s² and 2.47 m/s² for CarR and CarL, respectively).

Three training video clips were shown prior to the experimental video clips, to let the participants familiarize themselves with the task and the virtual environment. The first one contained only CarF. In the second video clip, there was only CarR which behaved the same as it did during the scenario 'R passes'. In the third clip, there was only CarL which behaved the same as CarR in scenario 'R passes' but from the left. During the training clips, the cyclist had a speed of 25 km/h. Additionally, six decoy video clips were played during the experiment to minimize the impression that there was always a car from the right. In the first decoy scenario, there was only CarL; CarL came to a full stop, just as CarL in scenario 'R&L stop'. In the second decoy scenario, neither CarR nor CarL appeared. These decoy scenarios were also combined with the three different cycling speeds. These six decoy scenarios were not included in the present analyses.

Each of the 12 experimental video clips was shown three times, and two decoy scenarios were shown once for each speed. Accordingly, participants viewed 45 videos (i.e., three training, thirty-six experimental, and six decoy video clips).

2.2.4. Procedure

First, the participants signed the consent form and read a form describing the task instructions and experimental procedures. The form stated that participants had to imagine themselves cycling in a simulated environment. Participants were instructed to indicate whether they *would cross the intersection first* or whether they *would not cross the intersection first* by pressing or releasing the spacebar during the video clip, respectively. The form clarified that the animation was not interactive. That is, participants' input did not influence the behavior of the bicycle. Furthermore, participants were informed that they had to press the spacebar at the beginning of the video (i.e., they *would cross the intersection first*) and that they could press/release the spacebar at any time and for as many times as they would need during the video clip. Finally, the form stated that participants would encounter three different cycling speeds '*slow: cycling speed on a conventional bicycle*', '*medium: cycling speed on a racing bicycle in an urban area*' and '*high: cycling speed on a racing bicycle in a rural area*' for 15, 25, and 35 km/h, respectively. Participants were not informed about the intersection scenarios.

At the beginning of the experiment, the eye tracker was calibrated using a nine-point calibration. All participants were initially shown three training clips. If necessary, instructions regarding the spacebar input were provided again. The experiment was divided into three sets of 14 animations, containing each of the 12 experimental clips and two of the six decoy clips. The 14 video clips were randomized per set using a pseudorandom generator.

Before each video clip, a screen was shown containing the task instructions and the speed of the cyclist in the upcoming animation. The following instructions were given: "*Press 'Space-bar' = 'I will cross the intersection first'; Release 'Space-bar' = 'I will not cross the intersection first'; Your velocity will be: Medium*". This screen was visible until the participant pressed the spacebar. First, a black screen with a fixation point located in

the middle was shown for approximately 1 s, and then the video clip automatically started. No feedback was provided during the experiment.

Following the presentation of the last animated video clip, participants completed a questionnaire containing questions about their background information and yielding behavior in four hypothetical scenarios (Section 2.2.5.3). The whole experiment lasted about 30 min.

2.2.5. Measures

2.2.5.1. Crossing judgments

Mean number of crossing judgment changes. This measure describes how many times the participants changed their crossing judgment when approaching the intersection. The mean number of crossing judgment changes was based on 108 trials (i.e., 36 participants x 3 repetitions) for each of the 12 conditions. The initial judgment was always 'I will cross the intersection first' (i.e., spacebar pressed). Note that the time between the video frame where CarR became visible until the end of the video clip was similar between the three cycling speeds (these durations ranged between 8.50 s and 9.90 s for the 12 videos depending on the intersection scenario and cycling speed).

2.2.5.2. Eye movements

The following measures were calculated as an average across 108 trials for each of the 12 conditions. The measures were calculated from the first video clip frame where part of CarR became visible till the frame where part of CarR disappeared from view or when the video clip ended (durations ranged between 7.80 s and 9.90 s depending on the intersection scenario and cycling speed). Dynamic areas of interest (AOIs) were used to determine whether the participants were looking at CarR or CarL. The AOIs were defined using vertical lines with a 70-pixel margin on the front of the car, and a 35-pixel margin on the rear of the car (Fig. 2.1 right).

Dwell time percentage (% of time). This measure represents the percentage of time spent looking at the AOI.

Frequency of entry fixations (Hz). This measure describes the frequency at which the participants' eyes entered and fixated on the AOI.

Mean fixation duration (s). This measure is the average of durations of all fixations on the AOI.

2.2.5.3. Self-reported yielding behavior

Four yielding behavior items were developed, based on Houtenbos (2008), who studied driver behavior at intersections that are not regulated by traffic signs. Participants were asked whether they would take priority in four scenarios (see Table 2.1), and marked their responses by ticking one of the three options: yes, no, unsure.

2.2.6. Analyses

2.2.6.1. Processing of crossing judgment and eye-tracking data

One male participant was excluded from the analysis due to a misunderstanding of the crossing judgment task. Data checks further revealed that participants in 14.5% of the 'R passes' trials (out of 324) indicated that they would cross the intersection first at the end of the video clip, even though the car in this scenario had crossed the intersection first. This could mean that these participants interpreted the spacebar task as 'I want to cross the intersection now' rather than 'I would cross the intersection first'. Because such potential misinterpretation does not invalidate the results before entering the intersection, these trials were retained in the analysis.

The eye tracker provided the participants' gaze coordinates on the screen. First, eye blinks were removed through linear interpolation. Extraneous noise in horizontal (x) and vertical (y) directions was filtered using a median filter with a frame size of 100 ms. Second, eye movements were classified into fixations and saccades. A saccade was defined as an interval in which the eye movement speed exceeded 2000 pixels/s (after smoothing of the gaze speed using a 2nd order Savitzky-Golay filter with a 20 ms frame size, i.e., 41 samples at 2000 Hz). Fixations shorter than 40 ms (see also Nyström & Holmqvist, 2010) and fixations longer than 5.0 s (indicating prolonged staring towards one point in the scene) were removed from the analysis.

2.2.6.2. Analyses and statistical tests

Because the videos featured a dynamic chain of events, we first visualized participants' crossing judgments and eye movements as a function of elapsed time in the video clip to gain an insight into participants' aggregate hazard anticipation. Next, we proceeded with an analysis of averages calculated across the time windows when CarR was visible. Differences between the 12 conditions were analyzed with two-way repeated measures analyses of variance (ANOVA). First, an ANOVA was performed with the car approach scenario ('R passes' vs. 'R collision' vs. 'R stops') and the cycling speed (15 km/h vs. 25 km/h vs. 35 km/h), as independent variables. Second, an ANOVA was performed with traffic complexity (CarR in 'R stops' vs. CarR in 'R&L stop') and cycling speed (15 km/h vs. 25 km/h vs. 35 km/h) as independent variables. The effect size was reported as partial eta squared, η^2 (Cohen, 1988).

2.3. Results

2.3.1. Self-reported yielding behavior

The results for the yielding behavior questionnaire (Table 2.1) showed that none of the participants would take priority if a car from the right does not slow down, whereas 11% of the participants reported taking priority if the car from the right does slow down. The percentage of participants who reported taking priority was higher when the car would approach from the left as compared to when the car would approach from the right

(8% vs. 0% and 92% vs. 11% for the car does not slow down and the car slows down, respectively).

Table 2.1. Self-reported yielding behavior ($n = 36$) in four scenarios. Dashed lines indicate that the car slows down and the solid lines indicate that the car does not slow down.

Would you take priority?	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Yes	0%	11%	8%	92%
No	97%	58%	72%	3%
Unsure	3%	31%	20%	5%

2.3.2. Crossing judgments

As can be seen in Fig. 2.2, participants changed their initial 'I will cross first' judgment to 'I will not cross first' judgment within 2 s after CarR appeared from behind the building in approximately two-thirds of the trials, for each of the 12 conditions. The crossing judgments had a similar pattern for the three cycling speeds, but there were clear differences between the four scenarios (Fig. 2.2).

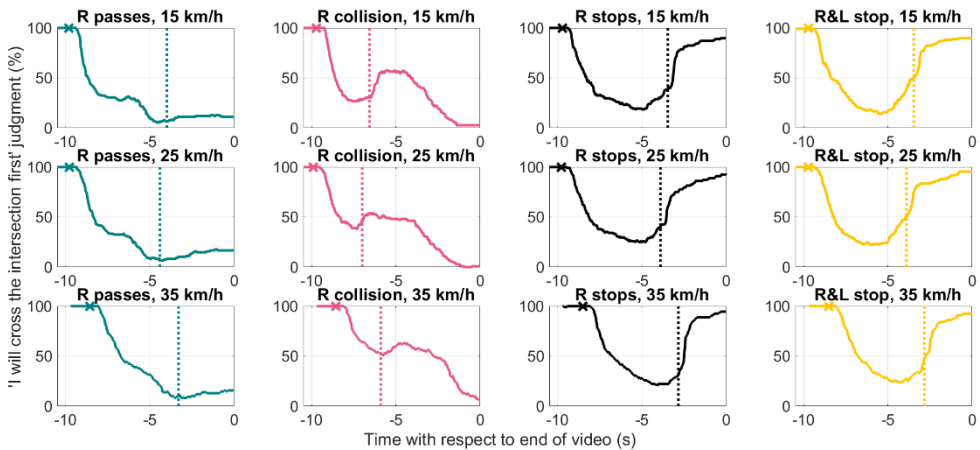


Fig. 2.2. Percentage of 'I will cross first' judgments for the four intersection scenarios at three cycling speeds. The 'x' symbols at the left top indicate when CarR became visible. The vertical lines indicate the moment when CarR entered the intersection ('R passes' scenario), stopped decelerating and continued moving at a constant speed of 10 km/h ('R collision' scenario), or came to a full stop ('R stops' and 'R&L stop' scenarios).

In the 'R passes' scenario, the 'I will cross first' judgment showed a decreasing trend from 100% to about 10%. In the 'R stops' and 'R&L stop' scenarios, the majority of the participants changed their initial 'I will cross first' judgment to 'I will not cross first' judgment, and changed back to 'I will cross first' after CarR had come to a stop (Fig. 2.2). In the 'R collision' scenario, participants were more likely to indicate 'I will cross first' judgment while CarR was approaching the intersection compared to the other three scenarios. This can be explained by the strong deceleration from 40 km/h to 10 km/h after which CarR continued moving slowly at 10 km/h (see the rise after the pink vertical line in Fig. 2.2). When CarR got closer to the intersection, participants gradually changed their judgment to 'I will not cross first', as it became clear that CarR would enter the intersection before the cyclist.

Table 2.2. Number of trials in which participants' judgment changed (from 'I will cross first' to 'I will not cross first', or from 'I will not cross first' to 'I will cross first') ($n = 108$ trials for each row), and mean and standard deviation of the mean number of judgment changes at the level of the participants ($n = 36$).

	0 changes	1 change	2 changes	3 changes	4 changes	5 or 7 changes	Number of judgment changes Mean (SD)
	<i>I will cross first</i>	<i>I will not cross first</i>	<i>I will cross first</i>	<i>I will not cross first</i>	<i>I will cross first</i>	<i>I will not cross first</i>	
R passes 15 km/h	0	88	10 ¹	8	2 ¹	0	1.30 (0.52)
R passes 25 km/h	4 ¹	87	13 ¹	3	1 ¹	0	1.17 (0.35)
R passes 35 km/h	3 ¹	84	14 ¹	5	0	2	1.27 (0.49)
R collision 15 km/h	1	60	2	40	0	5	1.94 (0.89)
R collision 25 km/h	0	73	1	32	0	2	1.68 (0.80)
R collision 35 km/h	2	74	3	23	2	4	1.66 (0.87)
R stops 15 km/h	13	11	78	0	6	0	1.77 (0.62)
R stops 25 km/h	19	8	79	1	1	0	1.60 (0.60)
R stops 35 km/h	18	6	80	0	4	0	1.69 (0.65)
R&L stop 15 km/h	11	11	81	1	4	0	1.81 (0.61)
R&L stop 25 km/h	18	5	83	0	2	0	1.66 (0.64)
R&L stop 35 km/h	17	8	78	0	5	0	1.70 (0.67)

Notes. The final judgment for each spacebar change is indicated in Italics.

¹ The opposite judgment from what would be expected (i.e., the participant did not cross the intersection first in the animated video clip).

On average (Table 2.2), participants changed their judgments the lowest number of times in the 'R passes' scenarios (mean = 1.24, $SD = 0.33$), followed by 'R stops' (mean = 1.69, $SD = 0.52$), 'R&L stop' (mean = 1.72, $SD = 0.57$), and 'R collision' (mean = 1.76, $SD = 0.69$). The number of crossing judgment changes significantly differed between three car approach scenarios ($F(2,70) = 13.638$, $p < 0.001$, $\eta^2 = 0.280$). Furthermore, participants changed their crossing judgment more times when watching video clips at 15 km/h compared to other two speeds ($F(2,70) = 5.009$, $p = 0.009$, $\eta^2 = 0.125$). The interaction 'car approach scenario x cycling speed' was not significant ($p = 0.663$).

There was no significant effect of traffic complexity ($F(1,35) = 0.680$, $p = 0.415$, $\eta^2 = 0.019$) nor of cycling speed ($F(2,70) = 2.823$, $p = 0.066$, $\eta^2 = 0.075$) on the number of crossing judgment changes in the two stop scenarios. The interaction 'traffic complexity x cycling speed' was not significant either ($p = 0.959$).

2.3.3. Eye movements

2.3.3.1. Gaze distribution

Fig. 2.3 shows the aggregate distributions of the 12 conditions of participants' horizontal eye movements. In all 12 conditions, participants looked mostly straight ahead and sampled both crossroads before CarR appeared. Gaze was directed primarily (about 80% in all 12 conditions) at CarR right after the car appeared in view. The participants spent more time looking at CarR than at the road ahead or at the left crossroad during the time interval when CarR was approaching the intersection.

Differences in gaze distribution between the scenarios occurred when the car was close to the intersection. In 'R passes', the dwell time percentage on CarR was about 95% when the car entered the intersection, and dropped quickly after the car had crossed the intersection. In 'R stops', a maximum dwell time of 95% was reached just before the car came to a standstill, and dropped quickly afterward. In 'R collision', the dwell time percentage on CarR increased to nearly 100% when CarR entered the intersection.

Participants distributed their gaze comparably between CarR and CarL when both cars were moving (Fig. 2.3). Similar to 'R stops', participants in 'R&L stop' reduced glancing at CarL directly after it came to a standstill. A maximum dwell time percentage of around 40% on CarL was reached prior to when the car came to a full stop, after which participants primarily directed their gaze to the moving CarR. Overall, the dwell time percentage was higher on CarR than on CarL.

Figs. 2.4 and 2.5 show that participants' dwell time percentage on CarR was higher in 'R collision' (mean = 77.28%, $SD = 8.40$) than in 'R passes' (mean = 66.83%, $SD = 7.66$), 'R stops' (mean = 64.76%, $SD = 10.12$), and 'R&L stop' (mean = 46.62%, $SD = 9.00$). The dwell time percentage strongly and significantly differed between three car approach scenarios ($F(2,70) = 73.384$, $p < 0.001$, $\eta^2 = 0.677$) but it did not significantly differ between three cycling speeds ($F(2,70) = 1.683$, $p = 0.193$, $\eta^2 = 0.046$). The interaction effect 'car approach scenario x cycling speed' was small yet statistically significant ($F(4,140) = 2.768$, $p = 0.030$, $\eta^2 = 0.073$). In 'R stops', dwell time percentage on CarR decreased with increasing speed, whereas speed did not clearly affect dwell time percentage in 'R passes' and 'R collision' (Fig. 2.4 top).

Concerning traffic complexity, the dwell time percentage on CarR was lower in 'R&L stop' compared to 'R stops' (Fig. 2.5 top). This was supported by an ANOVA, indicating a strong and significant effect of traffic complexity ($F(1,35) = 271.555$, $p < 0.001$, $\eta^2 = 0.886$) and a moderate effect of cycling speed ($F(2,70) = 10.901$, $p < 0.001$, $\eta^2 = 0.237$), whereas the interaction effect 'traffic complexity x speed' was not significant ($p = 0.910$).

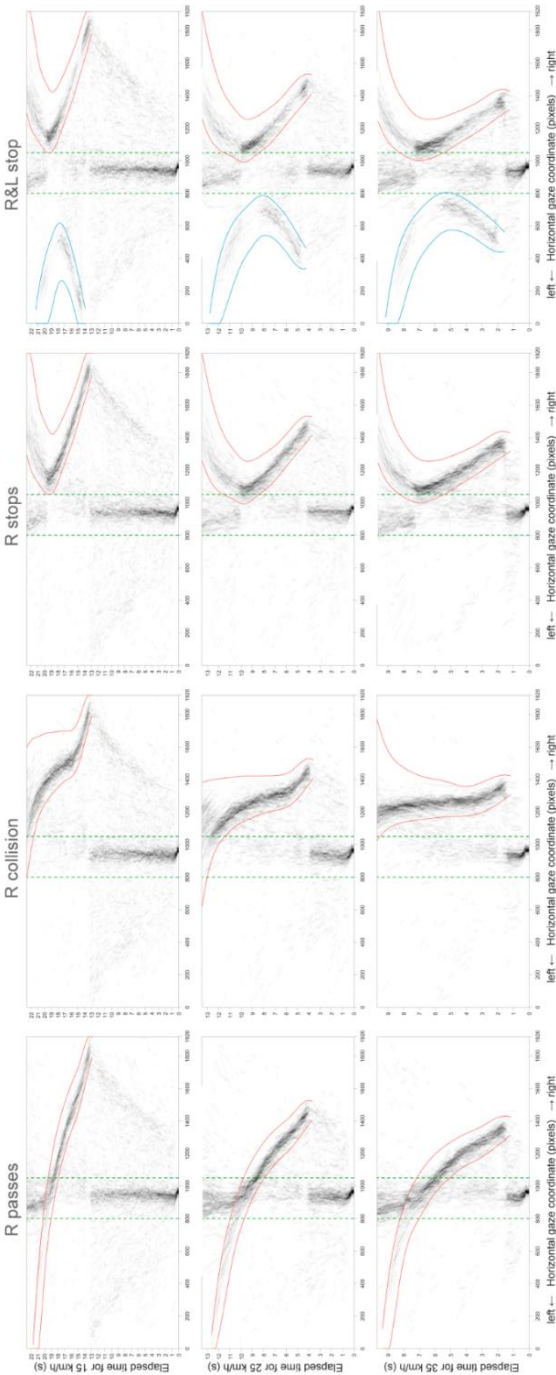


Fig. 2.3. Distribution of the horizontal gaze coordinate for the four intersection scenarios at three cycling speeds. The grayscale runs from 0 (no sampling at that coordinate) to 1 (maximum value between 1 s to the end of the video clip). The red and blue lines represent the AOIs of CarR and CarL, respectively. The dashed vertical lines represent the approximate boundaries of the road.

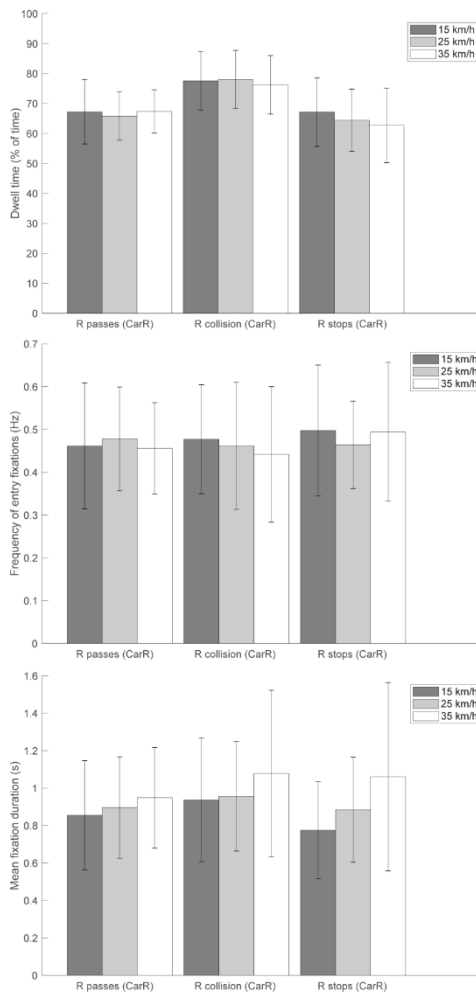


Fig. 2.4. Dwell time (top), frequency of entry fixations (middle), and mean fixation duration (bottom) for three car approach scenarios at three cycling speeds. The corresponding AOI is mentioned in parentheses. The error bars represent the mean \pm 1 standard deviation across the 36 participants.

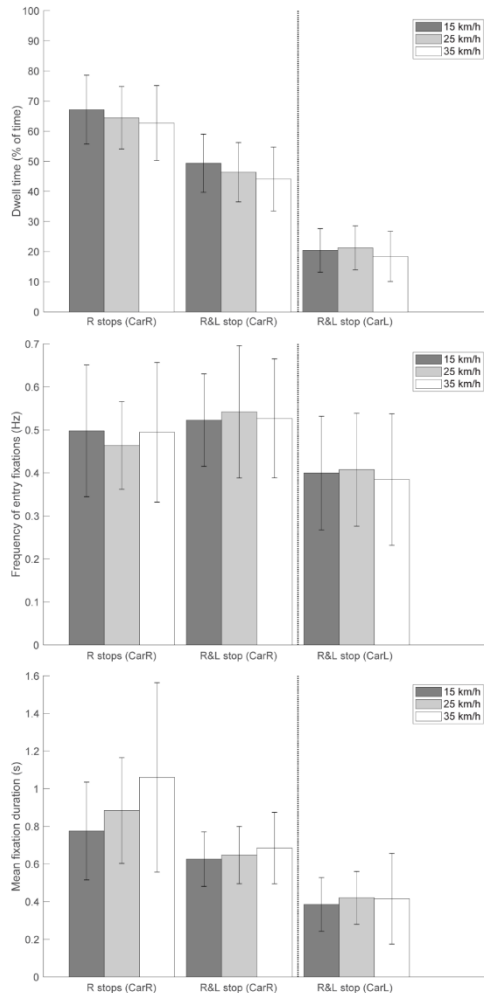


Fig. 2.5. Dwell time (top), frequency of entry fixations (middle), and mean fixation duration (bottom) for two traffic complexity conditions at three cycling speeds. The corresponding AOI is mentioned in parentheses. The error bars represent the mean \pm 1 standard deviation across the 36 participants.

2.3.3.2. Entry fixations

As shown in Fig. 2.4 (middle), participants fixated on CarR at similar frequencies in 'R passes' (mean = 0.47, *SD* = 0.11), 'R collision' (mean = 0.46, *SD* = 0.13), and 'R stops'

(mean = 0.49, $SD = 0.13$). Further, participants fixated on CarR at slightly higher frequency in 'R&L stop' (mean = 0.53, $SD = 0.11$) compared to 'R stops' indicating that traffic complexity resulted in higher eye-movement activity (Fig. 2.5 middle). In addition, participants fixated at lower frequency CarL compared to CarR in 'R&L stop'.

There were no statistically significant differences in the frequency of entry fixations on CarR between three car approach scenarios ($F(2,70) = 1.943$, $p = 0.151$, $\eta^2 = 0.053$) and neither between the three cycling speeds ($F(2,70) = 0.854$, $p = 0.430$, $\eta^2 = 0.024$). The interaction effect 'car approach scenario x cycling speed' was not significant ($p = 0.117$).

An ANOVA showed a significant effect of traffic complexity ($F(1,35) = 9.833$, $p = 0.003$, $\eta^2 = 0.219$) and no significant effect of speed ($F(2,70) = 0.216$, $p = 0.806$, $\eta^2 = 0.006$) on the frequency of entry fixations to CarR in the two stop scenarios. The interaction effect 'traffic complexity x cycling speed' was not significant ($p = 0.163$).

2.3.3.3. Fixation duration

The mean fixation duration on CarR varied as a function of elapsed time in the video clips (Fig. 2.6). In 'R passes', participants showed relatively long fixations on CarR when the car was approaching the intersection, and fixation durations decreased after CarR had entered the intersection. In 'R stops', participants showed elevated fixation durations on CarR just before CarR came to a standstill at the intersection. In 'R collision', fixation durations on CarR were high during the entire period when CarR was approaching the intersection. Finally, in 'R&L stop', participants showed short fixations on CarR when CarR was approaching the intersection (presumably because attention had to be shared with CarL, which was approaching at the same time), but long fixations just before CarR came to a standstill (as in 'R stops' scenario).

Compared to 'R stops', participants in 'R&L stop' showed shorter fixation durations on CarR (Fig. 2.5 bottom), but the mean fixation durations followed the same pattern. Fig. 2.5 (bottom) shows that mean fixation durations on CarL were lower than mean fixation durations on CarR.

Fixation durations on CarR were higher in 'R collision' (mean = 0.99, $SD = 0.30$) compared to 'R passes' (mean = 0.90, $SD = 0.22$) and 'R stops' (mean = 0.91, $SD = 0.28$). In 'R&L stop', participants' fixation durations on CarR were the shortest (mean = 0.65, $SD = 0.13$). Mean fixation durations on CarR (Fig. 2.4 bottom) significantly differ between the three car approach scenarios ($F(2,70) = 3.800$, $p = 0.027$, $\eta^2 = 0.098$). The fixation durations were significantly longer when cycling speed was higher ($F(2,70) = 11.795$, $p < 0.001$, $\eta^2 = 0.252$). The interaction effect 'car approach scenario x cycling speed' was not significant ($p = 0.171$).

Traffic complexity (i.e., 'R stops' vs. 'R&L stop') resulted in shorter fixation durations on CarR (Fig. 2.5 bottom). The ANOVA showed a significant effect of traffic complexity ($F(1,35) = 61.016$, $p < 0.001$, $\eta^2 = 0.635$) and speed ($F(2,70) = 9.671$, $p < 0.001$, $\eta^2 = 0.216$) on the mean fixation duration in the two stop scenarios. The interaction effect 'traffic complexity x cycling speed' was significant ($F(2,70) = 5.901$, $p = 0.004$, $\eta^2 = 0.144$).

This interaction effect is because the fixation duration on CarR increased with increasing speed in 'R stops', yet was relatively similar for the three speeds in 'R&L stop' (Fig. 2.5).

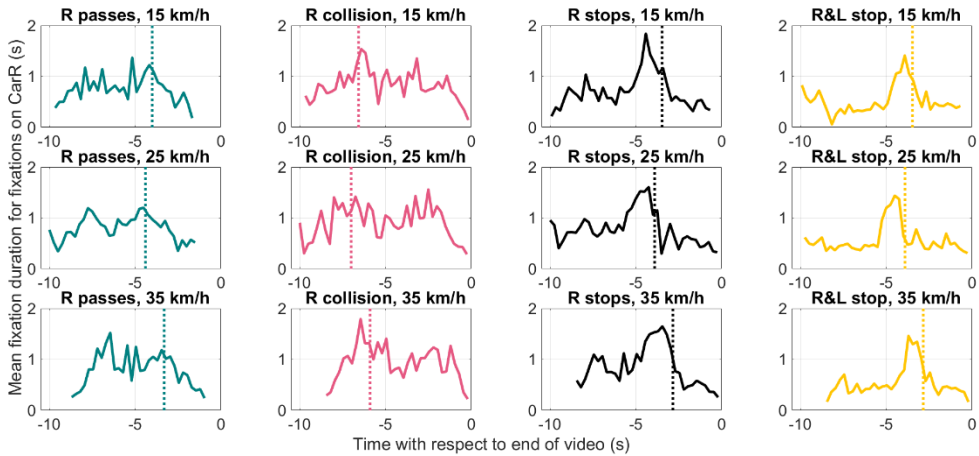


Fig. 2.6. Mean fixation duration on CarR as a function of elapsed video time for the four intersection scenarios at three cycling speeds. The vertical lines indicate the moment when CarR entered the intersection ('R passes' scenario), stopped decelerating and continued moving at a constant speed of 10 km/h ('R collision' scenario), or came to a full stop ('R stops' and 'R&L stop' scenarios). Data are shown from when CarR became visible from behind the building until the car disappeared from the view, or when the video clip stopped. Mean fixation durations are calculated per bin of 250 ms.

2.3.4. Combined analysis of eye movements and crossing judgments

Above, we analyzed whether participants looked at CarR (dwell time in Figs. 2.4 and 2.5, heat maps in Fig. 2.3) and whether participants indicated to cross the intersection first or not as the situation evolved (Fig. 2.2). In this section, we provide a more in-depth analysis of the interaction between gaze behavior and crossing judgments. More specifically, Fig. 2.7 shows whether (green lines) or not (black lines) participants were looking at CarR while indicating 'I will cross first' (solid lines) or 'I will not cross first' (dotted lines) as a function of elapsed time.

In 'R passes', participants were likely to look at CarR and indicate 'I will not cross first' judgment before CarR crossed the intersection (i.e., a high value of the green dotted line). After CarR passed the intersection, participants often did not look at CarR anymore while still indicating 'I will not cross first' judgment (i.e., a high value of the black dotted line).

In 'R stops' scenario, participants looked at CarR and indicated 'I will not cross first' judgment before CarR stopped (i.e., a high value of the green dotted line). After CarR had stopped, participants looked considerably less at the car and indicated they would

cross first (i.e., a relatively high value of the black solid line). Participants were looking less at CarR in 'R&L stop' than in 'R stops' while indicating their crossing judgment (i.e., a relatively high value of black dotted line). The results for the 'R&L stop' scenario were similar to the 'R stops' scenario after CarL had come to a stop.

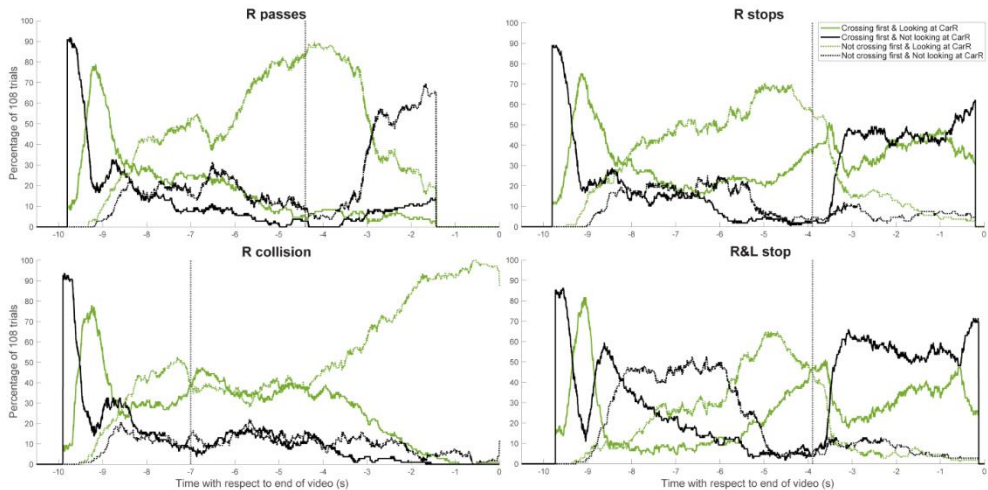


Fig. 2.7. Percentage of trials in which participants looked (green lines) or did not look (black lines) at CarR while indication 'I will cross first' (solid lines) or 'I will not cross first' (dotted lines) judgments as a function of elapsed video time for four intersection scenarios for cycling speed of 25 km/h. The vertical lines indicate the moment when CarR entered the intersection ('R passes' scenario), stopped decelerating and continued moving at a constant speed of 10 km/h ('R collision' scenario), or came to a full stop ('R stops' and 'R&L stop' scenarios). The four reported percentages add up to 100%. Results follow a similar pattern for the other two cycling speeds (see Supplementary material).

Regarding 'R collision', it can be seen that participants were looking at CarR in a high percentage of trials regardless of their judgment input (i.e., high values of both green lines). To illustrate, between -7 s and -4.5 s, approximately half of the participants were indicating the 'I will cross first' judgment whereas the other half indicated 'I will not cross first' judgment (Fig. 2.7), suggesting that participants kept looking at CarR because they were uncertain about whether CarR would cross first. Near the end of the video clip, nearly all participants looked at CarR and made 'I will not cross first' judgment (i.e., a high value of the green dotted line).

2.4. Discussion

Accident statistics indicate that crashes between cyclists and car drivers at intersections occur even when the cyclist must have seen the approaching car, suggesting the importance of hazard anticipation issues and expectancy (Räsänen &

Summala, 1998). To understand how cyclists anticipate potential hazards at intersections, we examined how the motion of an approaching car (culminating in safe and collision scenarios between the cyclist and the car) and traffic complexity (i.e., one versus two approaching cars) are associated with cyclists' eye movements and crossing judgments. Further, we investigated the effect of the cyclist's approach speed on visual patterns and crossing judgments.

In line with Van Loon et al. (2010), participants spent more time looking at the approaching car(s) than to the rest of the visual scene. Participants looked at the approaching car when the car was still relevant to the task of crossing the intersection and focused on the road ahead when the car did not pose an imminent hazard anymore. Once the car had stopped (as shown in 'R stops' and 'R&L stop' scenarios) or once the car had passed the intersection (as shown in 'R passes') participants paid considerably less attention to it. In 'R collision', participants kept looking at the car until the end of the video clip even when they already indicated they would not cross the intersection first. We conclude that cyclists ignore the car and direct their attention to the road ahead only when they can be certain that the car does not pose a threat.

Fixation durations were elevated right before the car came to a full stop or entered the intersection. This may reflect in-depth processing (Crundall et al., 1999, 2002; Chapman & Underwood, 1998; Velichkovsky et al., 2002) whereby the cyclist tries to ascertain whether the car stops or not. In addition, significantly longer fixations were observed in the collision scenario compared to the two safe scenarios, suggesting a narrowing focus to the threatening object (Underwood et al., 2003).

As expected, traffic complexity resulted in divided attention between two approaching cars and gazing to the right car at a higher frequency. After the car approaching the intersection from the left had stopped, participants focused their attention predominantly on the right car, which still posed a hazard and had higher relevance to the crossing task. Even though participants spent less time looking at the car from the right and also fixated it with shorter durations at higher traffic complexity, there were no significant differences in crossing judgments between the two traffic complexities. This suggests that participants made their judgments based on the car that had a higher relevance to the task (in this case the right car). This finding is consistent with the self-reports, in which participants were more likely to yield to a car approaching from the right than to a car from the left.

Participants changed their initial "I will cross the intersection first" judgment once the car from the right appeared in view and updated this judgment based on how the traffic situation unfolded. These findings indicate that both visual information (i.e., bottom-up cues) and expectancies (i.e., top-down cues) guide cyclists' crossing judgments (see also Underwood, 2007). In approximately two-thirds of the trials, participants indicated that they would not cross the intersection first once the right car had appeared from behind the building (see Fig. 2.2), which is consistent with the self-reported yielding behavior (see Table 2.1) which showed that participants are likely to yield to a car having right of way (i.e., a car from the right). The participants updated their crossing judgments when

relevant discrete events (i.e., car stopping, car passing the intersection) occurred in the environment. These results can be interpreted using gap acceptance research (e.g., Chihak et al., 2010; Louveton et al., 2012) which showed that when road users approach an intersection, they first slow down (a period where they can be assumed to gaze at the approaching vehicle) and accelerate to cross the gap at the right time. Similarly, directly after the discrete event, participants in our study stopped looking at the approaching car and indicated that they would like to cross.

The results from the present study indicate that cyclists are responsive to discrete events. However, a clear perceptual event did not occur in the collision scenario, which involved ongoing uncertainty about whether the car would stop or not. Cyclists might expect that a car having right of way is yielding when it has slowed down, while in fact, the driver might not slow down because of the cyclist (Summala & Räsänen, 2000). Our results of the 'Collision R' scenario are representative of this problem, as participants were likely to provide "I will cross the intersection first" judgments while the vehicle was slowing down yet not yielding to the cyclist. More research should be conducted to understand which visual cues cyclists should pick up to be able to predict hazardous outcomes at intersections.

Overall, participants spent a similar amount of time looking at the car even though the cycling speeds were vastly different (15, 25, and 35 km/h). The results showed moderate but statistically significant effects of cycling speed on the fixation duration, with higher speeds corresponding to longer fixation durations. One plausible explanation for the lack of strong effects of cycling speed on cyclists' eye movements is that cycling speeds are considerably lower than typical driving speeds; in driving tasks it has been found that drivers reduce their horizontal gaze variability as driving speeds increase (Rogers et al., 2005; Van Leeuwen et al., 2015). Another explanation is that participants did not have to control the bicycle, and so could safely direct their visual attention away from the road. Small differences in the number of crossing judgment changes were found between the three speeds. However, the same pattern of crossing judgment changes was observed across all three cycling speeds suggesting that participants' crossing judgments were governed by the motion of the car rather than by cycling speed.

Several limitations have to be taken into account when interpreting the results of this study. First, we asked participants to indicate their crossing judgment by means of the spacebar. This task may have been confusing because video clips were non-interactive. In reality, it may be more intuitive to brake prior to entering the intersection than to indicate who will cross the intersection first. Second, the participants were watching the videos on a computer screen with a limited field of view and a simple virtual environment. A large field of view and being involved in a physical cycling task may enhance situation awareness compared to passive observation. This limitation could be addressed by using an immersive cycling simulator (e.g., Chihak et al., 2010; Grechkin et al., 2013). Third, in this study, we manipulated only the car's motion, whereas in reality a cyclist can extract various visual cues that are indicative of a driver's intentions, such as arm motion, lighting the high beams, eye contact, and head movement (e.g., Renge, 2000). Fourth,

participants watched video clips while not controlling the bicycle. The actual control of a bicycle may place additional demands on a person's gaze behavior, as the road ahead might be more relevant to scan for active cyclists than for passive viewers (Zeuwts et al., 2016). Mackenzie and Harris (2015) found that scan patterns were wider for participants whom we asked to observe the road as compared to participants were asked to drive themselves. Thus, it is possible that the passive viewing of the video clips allowed our participants to gaze longer on the right and left roads where the approaching cars were located than it would be possible when controlling a bicycle. Finally, the role of traffic complexity and traffic rules deserves further investigation. In this study, CarR always had right of way and CarL always stopped. In reality, intersections can be busier and a car driver without right of way can violate traffic rules.

2.5. Conclusions and recommendations

In conclusion, visual behavior and crossing judgments of cyclists approaching uncontrolled intersections differ between situational aspects of safe and collision outcomes, locations of cars at the intersection, and traffic complexity. Cyclists are more inclined to look at a car that is on a collision course (i.e., a car approaching an intersection) than at a car that has already passed an intersection or a car that has stopped in front of the intersection. The effect of cycling speed on dwell time, fixation durations, and crossing judgments is small to moderate.

It remains to be investigated which cues guide cyclists' anticipation and whether cyclists can perform a satisfactory braking maneuver in collision scenarios where the driver has not seen the approaching cyclist. Knowledge of cyclists' gaze and crossing behavior in safe and collision scenarios could prove useful in the development of training programs for cyclists, as well as in the design of intersection warning systems and vehicle-to-vehicle communication technologies.

Supplementary material

Supplementary data, scripts, and video clips are available at <https://doi.org/10.4121/uuid:1d8ddcd0-5139-4ada-81a1-9f34c9f70c88>.

References

- Åberg, L. (1998). Traffic rules and traffic safety. *Safety Science*, 29, 205–215.
- Akhtar, J., Aust, M. L., Eriksson, R. J., Fagerlind, H., Høye, A., Phillips, R., & Sagberg, F. (2010). *Factors contributing to road fatalities* (TØI Report 1067/2010). Oslo: TØI Institute of Transport Economics.
- Buswell, G. T. (1935). *How people look at pictures: A study of psychology of perception in art*. Chicago: The University of Chicago Press.
- Caird, J. K., & Hancock, P. A. (1994). The perception of arrival time for different oncoming vehicles at an intersection. *Ecological Psychology*, 6, 83–109.

- Chapman, P. R., & Underwood, G. (1998). Visual search of driving situations: Danger and experience. *Perception*, 27, 951–964.
- Chihak, B. J., Plumert, J. M., Ziemer, C. J., Babu, S., Grechkin, T., Cremer, J. F., & Kearney, J. K. (2010). Synchronizing self and object movement: How child and adult cyclists intercept moving gaps in a virtual environment. *Journal of Experimental Psychology: Human Perception and Performance*, 36, 1535–1552.
- Choi, E. H. (2010). *Crash factors in intersection-related crashes: An on-scene perspective* (Report No. DOT HS 811 366). Washington: NHTSA National Highway Traffic Safety Administration.
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. New York: Academic Press.
- Crundall, D., Underwood, G., & Chapman, P. (1999). Driving experience and the functional field of view. *Perception*, 28, 1075–1087.
- Crundall, D., Underwood, G., & Chapman, P. (2002). Attending to the peripheral world while driving. *Applied Cognitive Psychology*, 16, 459–475.
- Crundall, D., Humphrey, K., & Clarke, D. (2008). Perception and appraisal of approaching motorcycles at junctions. *Transportation Research Part F: Traffic Psychology and Behaviour*, 11, 159–167.
- Dozza, M., Piccinini, G. F. B., & Werneke, J. (2016). Using naturalistic data to assess e-cyclist behavior. *Transportation Research Part F: Traffic Psychology and Behaviour*, 41, 271–226.
- Ebbesen, E. B., Parker, S., & Konečni, V. J. (1977). Laboratory and field analyses of decisions involving risk. *Journal of Experimental Psychology: Human Perception and Performance*, 3, 576–589.
- Endsley, M. R. (1995). Toward a theory of situation awareness in dynamic systems. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 37, 32–64.
- Grechkin, T. Y., Chihak, B. J., Cremer, J. F., Kearney, J. K., & Plumert, J. M. (2013). Perceiving and acting on complex affordances: How children and adults bicycle across two lanes of opposing traffic. *Journal of Experimental Psychology: Human Perception and Performance*, 39, 23–36.
- Hancock, P. A., & Manster, M. P. (1997). Time-to-contact: More than tau alone. *Ecological Psychology*, 9, 265–297.
- Hendriksen, I., Engbers, L., Schrijver, J., Gijlswijk, R. V., Weltevreden, J., & Wiltling, J. (2008). *Elektrisch Fietsen: Marktonderzoek en verkenning toekomstmogelijkheden* [Electric bicycles: Market research and investigation.] (Report KvL/B&G/2008.067). Leiden: TNO.
- Herslund, M.-B., & Jørgensen, N. O. (2003). Looked-but-failed-to-see-errors in traffic. *Accident Analysis & Prevention*, 35, 885–891.
- Houtenbos, M. (2008). Expecting the unexpected: A study of interactive driving behaviour at intersections. Doctoral Dissertation, Delft University of Technology, the Netherlands.

- Lobjois, R., Benguigui, N., & Cavallo, V. (2013). The effects of age and traffic density on street-crossing behavior. *Accident Analysis & Prevention*, *53*, 166–175.
- Loftus, E. F., Loftus, G. R., & Messo, J. (1987). Some facts about “weapon focus”. *Law and Human Behavior*, *11*, 55–62.
- Louveton, N., Bootsma, R. J., Guerin, P., Berthelon, C., & Montagne, G. (2012). Intersection crossing considered as intercepting a moving traffic gap: Effects of task and environmental constraints. *Acta Psychologica*, *141*, 287–294.
- Mackenzie, A. K., & Harris, J. M. (2015). Eye movements and hazard perception in active and passive driving. *Visual Cognition*, *23*, 736–757.
- Mackworth, N. H., & Morandi, A. J. (1967). The gaze selects informative details within pictures. *Perception & Psychophysics*, *2*, 547–552.
- Methorst, R., Schepers, J. P., & Vermeulen, W. M. (2011). *Snorfiets op het fietspad* [Light mopeds on the bicycle path]. Delft: Ministry of Infrastructure and Environment.
- Näätänen, R., & Summala, H. (1974). A model for the role of motivational factors in drivers' decision-making. *Accident Analysis & Prevention*, *6*, 243–261.
- Najm, W. G., Koziol Jr., J. S., Tijerina, L., Pierowicz, J. A., Hendricks, D. L. (1994). Comparative assessment of crash causal factors and IVHS countermeasures. In *Proceedings of the IVHS America 1994 Annual Meeting*. USA: Atlanta, Georgia.
- Nyström, M., & Holmqvist, K. (2010). An adaptive algorithm for fixation, saccade, and glissade detection in eyetracking data. *Behavior Research Methods*, *42*, 188–204.
- Özkan, T., & Lajunen, T. (2005). A new addition to DBQ: Positive driver behaviours scale. *Transportation Research Part F: Traffic Psychology and Behaviour*, *8*, 355–368.
- Pai, C. W. (2011). Motorcycle right-of-way accidents—A literature review. *Accident Analysis & Prevention*, *43*, 971–982.
- Räsänen, M., & Summala, H. (1998). Attention and expectation problems in bicycle–car collisions: an in-depth study. *Accident Analysis & Prevention*, *30*, 657–666.
- Renge, K. (2000). Effect of driving experience on drivers' decoding process of roadway interpersonal communication. *Ergonomics*, *43*, 27–39.
- Rogers, S. D., Kadar, E. E., & Costall, A. (2005). Gaze patterns in the visual control of straight-road driving and braking as a function of speed and expertise. *Ecological Psychology*, *17*, 19–38.
- Rumar, K. (1985). The role of perceptual and cognitive filters in observed behavior. In L. Evans & R. C. Schwing (Eds.), *Human behavior and traffic safety* (pp. 151–170). New York: Plenum Press.
- Schepers, J. P., Kroeze, P. A., Sweers, W., & Wüst, J. C. (2011). Road factors and bicycle–motor vehicle crashes at unsignalized priority intersections. *Accident Analysis & Prevention*, *43*, 853–861.
- Schleinitz, K., Petzoldt, T., Franke-Bartholdt, L., Krems, J., & Gehlert, T. (2017). The German Naturalistic Cycling Study—Comparing cycling speed of riders of different e-bikes and conventional bicycles. *Safety Science*, *92*, 290–297.

- Scott, H., Hall, L., Litchfield, D., & Westwood, D. (2013). Visual information search in simulated junction negotiation: gaze transitions of young novice, young experienced and older experienced drivers. *Journal of Safety Research*, *45*, 111–116.
- Simpson, G., Johnston, L., & Richardson, M. (2003). An investigation of road crossing in a virtual environment. *Accident Analysis & Prevention*, *35*, 787–796.
- Summala, H., Pasanen, E., Räsänen, M., & Sievänen, J. (1996). Bicycle accidents and drivers' visual search at left and right turns. *Accident Analysis & Prevention*, *28*, 147–153.
- Summala, H., & Räsänen, M. (2000). Top-down and bottom-up processes in driver behavior at roundabouts and crossroads. *Transportation Human Factors*, *2*, 29–37.
- Underwood, G. (2007). Visual attention and the transition from novice to advanced driver. *Ergonomics*, *50*, 1235–1249.
- Underwood, G., Chapman, P., Berger, Z., & Crundall, D. (2003). Driving experience, attentional focusing, and the recall of recently inspected events. *Transportation Research Part F: Traffic Psychology and Behaviour*, *6*, 289–304.
- Van Leeuwen, P. M., Happee, R., & De Winter, J. C. F. (2015). Changes of driving performance and gaze behavior of novice drivers during a 30-min simulator-based training. *Procedia Manufacturing*, *3*, 3325–3332.
- Van Loon, E. M., Khashawi, F., & Underwood, G. (2010). Visual strategies used for time-to-arrival judgments in driving. *Perception*, *39*, 1216–1229.
- Velichkovsky, B. M., Rothert, A., Kopf, M., Dornhöfer, S. M., & Joos, M. (2002). Towards an express-diagnostics for level of processing and hazard perception. *Transportation Research Part F: Traffic Psychology and Behaviour*, *5*, 145–156.
- Werneke, J., & Vollrath, M. (2012). What does the driver look at? The influence of intersection characteristics on attention allocation and driving behavior. *Accident Analysis & Prevention*, *45*, 610–619.
- Wickens, C. D., Helleberg, J., Goh, J., Xu, X., & Horrey, W. J. (2001). *Pilot task management: Testing an attentional expected value model of visual scanning* (Technical report no. ARL-01-14/NASA-01-7). Savoy, IL: University of Illinois, Aviation Research Lab.
- Zeuwts, L., Vansteenkiste, P., Deconinck, F., van Maarseveen, M., Savelsbergh, G., Cardon, G., & Lenoir, M. (2016). Is gaze behaviour in a laboratory context similar to that in real-life? A study in bicyclists. *Transportation Research Part F: Traffic Psychology and Behaviour*, *43*, 131–140.

CHAPTER 3

WHAT WILL THE CAR DRIVER DO? A VIDEO-BASED QUESTIONNAIRE STUDY ON CYCLISTS' ANTICIPATION DURING SAFETY-CRITICAL SITUATIONS

Many bicycle–car crashes are caused by the fact that the driver fails to give right of way to the cyclist. Although the car driver is to blame, the cyclist may have been able to prevent the crash by anticipating the safety-critical event and slowing-down. This study aimed to understand how accurate cyclists are in predicting a driver's right-of-way violation, which cues contribute to cyclists' predictions, and which factors contribute to their self-reported slowing-down behavior as a function of the temporal proximity to the conflict. 1030 participants were presented with video clips of nine safety-critical intersection situations, with five different video freezing moments in a between-subjects design. After each video clip, participants completed a questionnaire to indicate what the car driver will do next, which bottom-up and top-down cues they think they used, as well as their intended slowing-down behavior and perceived risk. The results showed that participants' predictions of the driver's behavior develop over time, with more accurate predictions (i.e., reporting that the driver will not let the cyclist cross first) at later freezing moments. A regression analysis showed that perceived high speed and acceleration of the car were associated with correctly predicting that the driver will not let the cyclist cross first. Incorrect predictions were associated with believing that the car has a low speed or is decelerating, and with reporting that the cyclist has right of way. Correctly predicting that the driver will not let the cyclist cross first and perceived risk were significant predictors of intending to slow down in safety-critical intersection situations. findings add to the existing knowledge on cyclists' hazard anticipation and could be used for the development of training programs as well as for cycling support systems.

Kováčsová, N., De Winter, J. C. F., & Hagenzieker, M. P. (2019). What will the car driver do? A video-based questionnaire study on cyclists' anticipation during safety-critical situations. *Journal of Safety Research*, 69, 11–21.

3.1. Introduction

A crucial skill for safe performance in traffic is the ability to anticipate future events quickly and accurately, in order to have sufficient time for decision-making and performing an appropriate action (Allen et al., 1971; Cumming, 1964; Horswill, 2016a). An in-depth crash analysis suggests that both cyclists and drivers make anticipation errors that result in emergency events on the road (Räsänen & Summala, 1998). Although several researchers have investigated the mechanisms that underlie drivers' errors in cyclist–driver conflicts (e.g., Herslund & Jørgensen, 2003; Räsänen & Summala, 2000; Summala et al., 1996), knowledge on cyclists' errors is sparse. Thus far, research indicates that a large proportion of crashes happen in situations where the cyclist does see the oncoming car but wrongly expects that the car driver will yield in accordance with traffic rules (Räsänen & Summala, 1998).

A cyclist processes top-down and bottom-up cues to determine what the driver on a collision course is going to do next (see Endsley, 1995; Summala & Räsänen, 2000). Top-down or “conceptually driven” cues consist of procedural knowledge and expectancies based on formal/informal traffic rules and previous experience (Allen et al., 1971; Shor, 1964; Summala & Räsänen, 2000; Theeuwes, 2000). Knowledge and expectancies create prototypical representations of intersection situations, called schemas or scripts (Minsky, 1975; Rumelhart, 2018; Schank & Abelson, 1977). Bottom-up or “data-driven” cues consist of perceptual features in the situation that a road user can perceive directly (see Gibson, 2015). A cyclist can extract the driver's intentions from the car speed and position on the road, the indicator lights, and the driver's head orientation and hand signals (e.g., Drury & Pietraszewski, 1979; Lee & Sheppard, 2016; Sun et al., 2015; Walker, 2005). In the situation where a car driver inappropriately takes right of way (such as observed in Räsänen & Summala, 1998), the cyclist has to deviate from the expected sequence of events (top-down cues) and extracts relevant visual information (bottom-up cues) to prevent a collision.

Recently, Lee and Sheppard (2016) conducted a study in which participants were asked to predict the intentions (i.e., continuing straight or turning) of cars and motorcycles at three-way intersections. The authors found that drivers were more accurate in judging turning maneuvers when the vehicle was indicating the turn compared to when the indicator was off. However, participants were also able to predict the vehicle's maneuver based on vehicle motion in the indicator-off condition. A previous interview study on safety-critical events in everyday cycling indicated that a high speed of the car is a cue that cyclists pick up before the potential conflict (Werneke et al., 2015).

In bicycle–car conflicts, responding quickly can make the difference between crashing or not crashing. Despite the highly dynamic nature of such conflicts, the existing studies do not address the temporal aspect of how road users anticipate upcoming safety-critical events. For example, in Lee and Sheppard's (2016) and Westerhuis and De Waard's (2017) studies, participants were presented with video clips of an approaching or leading road user that ended just before the road user made a maneuver. In this way, only

information until a single temporal moment was obtained, without providing an insight into the development of anticipation as a function of time.

Being able to anticipate other road users' intentions accurately is a critical precursor of successful decision-making in traffic. However, having excellent anticipatory skills is not enough for safe performance in traffic; safe performance also depends on the amount of risk one perceives and is willing to take in traffic (e.g., Brown & Groeger, 1988; Deery, 1999; Näätänen & Summala, 1974). Cyclists' perceived risk is known to be high in situations where cyclists interact with cars, when not having control over the outcome of the traffic situation, or when the predictability of traffic situation is low (Chaurand & Delhomme, 2013; Møller & Hels, 2008), such as in situations where a car driver fails to give right of way. Road users who perceive a relatively low level of risk are more likely to show risky behaviors in traffic (see Deery, 1999, for a review).

In the present study, participants were asked to watch video clips from a cyclist's perspective. Each video included a safety-critical intersection situation in which a car driver violated the formal traffic rules. To examine how the accuracy of cyclists' anticipation develops as a function of the temporal proximity to the collision, participants were presented with five clip freezing moments of each intersection situation in a between-subjects design. After each video clip, participants completed a questionnaire to indicate what the car driver will do next, which bottom-up and top-down cues they think they used, as well as their intended slowing-down behavior and perceived risk. To summarize, this study addressed the following three research questions:

1. How do cyclists' predictions of what a car driver will do next at an intersection develop prior to a near miss or a crash with that car?

The temporally closer the person is to the critical event, the more relevant visual information is available (see Farrow et al., 2005, for a temporal occlusion paradigm). Based on this presumption, we expected that the accuracy of cyclists' predictions of whether the car driver will let the cyclist cross first or not increases as a function of the temporal proximity to the conflict, with the highest accuracy when the cyclist is temporally closest to the conflict.

2. How do bottom-up and top-down cues guide cyclists' predictions of what a car driver will do next at an intersection in near-miss and crash intersection situations?

We expected that cyclists use both bottom-up cues (e.g., the speed and turn indicator of the car) and top-down (e.g., the right-of-way rule, previous experience) to predict a car driver's behavior at an intersection. Based on Räsänen and Summala (1998) and Summala and Räsänen (2000), we expected that relying on the right-of-way rules and thinking that the car has a low speed or is decelerating are related to incorrect predictions (i.e., predicting that the driver will yield to the cyclist).

3. How are the prediction of the car driver's behavior, subjectively perceived risk, participants' age, and cycling experience associated with self-reported slowing-down behavior in near-miss and crash intersection situations?

We expected that correctly predicting the car driver's behavior as well as a high level of perceived risk are predictive of the cyclist's self-reported slowing-down behavior. Lastly, in line with studies that have used objective measures of riding behavior (e.g., Crundall et al., 2013; Liu et al., 2009), we expected that age and cycling experience would be positively associated with self-reported slowing-down behavior in near-miss and crash intersection situations.

3.2. Method

3.2.1. Participants

A total of 1384 participants from 65 countries completed the study online using SurveyMonkey (the five most frequently reported countries of residence were the United States, Venezuela, Italy, Canada, and the United Kingdom). Participants were recruited through the crowdsourcing service CrowdFlower and through the social networking service Facebook between February 27 and August 21, 2017. 1030 individuals (374 females, 653 males, 3 unknown) who met eligibility and quality control criteria (i.e., older than 18 years, provided consent to the instructions, correctly answered the quality control items), and who did not indicate 'never' on the cycling frequency item were included in this study. The mean age of the remaining participants was 34.09 ($SD = 10.45$), ranging between 18 and 70 years.

Table 3.1. Reported cycling experience in the summertime and driving experience in the last 12 months.

Cycling frequency	Never	Less than once a month	Once a month to once a week	1–3 days a week	4–6 days a week	Every day	N/A
Number of participants	0	121	127	508	172	102	0
Weekly cycling mileage	0–5 km	6–10 km	11–30 km	31–90 km	91–150 km	More than 151 km	N/A
Number of participants	221	223	219	228	88	39	12
Driving frequency	Never	Less than once a month	Once a month to once a week	1–3 days a week	4–6 days a week	Every day	N/A
Number of participants	154	87	65	233	248	237	6
Yearly driving mileage	0 km	1–5,000 km	5,001–15,000 km	15,001–25,000 km	25,001–50,000 km	More than 50,001 km	N/A
Number of participants	130	316	227	194	106	40	17

On average, participants started to cycle at the age of 8.32 years ($SD = 4.58$), and 76.0% of the participants reported driving a car at least once a month (see Table 3.1 for an overview of participants' cycling and driving experience). The majority of participants (58.1%) indicated that the car is their primary mode of transport, followed by the bicycle (17.6%), public transport (13.8%), walking (7.8%), and other (2.7%). The majority of participants owned a city bike (52.8%) or mountain bike (42.4%). 254 participants

(24.7%) reported to have been involved in an accident as a cyclist at least once during the last three years, and 44 participants reported that some of the reported accidents happened with a motorized vehicle at an intersection. The Human Research Ethics Committee of the Delft University of Technology (Ethics application no. 151, 2017) approved the study.

3.2.2. Materials

Video clips from a cyclist's point of view were collected from publicly available YouTube postings. Clip segments in which the car was crossing a cyclist's path and was visible for at least 2 s prior to this crossing were selected. Nine safety-critical and one safe intersection situation were selected. Safety-critical situations were defined as situations that included an approaching car that was not giving right of way to the cyclist, resulting in a crash (five situations) or a near miss if a car crossed the bike path without giving a right of way and the cyclist braked (four situations). In the safe situation, the approaching car stopped in front of the bike path. The safe situation was included to assess whether participants could discriminate between safety critical and safe intersection situations. In addition, one extra video clip of a safe situation was extracted from YouTube postings, which was used as a practice video clip to familiarize participants with the task.

The intersection situations were recorded during daylight in real traffic on Dutch (intersection situations 1–5), Northern American (intersection situations 6–8), and Australian roads (intersection situations 9–10); see Table 3.2 for an overview of the 10 intersection situations. The video clips of two situations recorded on the Australian roads were horizontally flipped to follow right-hand traffic rules in all intersection situations. Cyclists formally had right of way in all 10 situations and were cycling on a bike path/lane in 9 of the 10 situations.

All downloaded video clips were stored at a frame rate of 29.97 fps. Using a video editing method proposed by Westerhuis and De Waard (2017), each video clip started with a frozen frame containing a 3 s countdown at the right bottom of the screen, after which the clip was played. Five clip freezing conditions of each clip were created using Adobe Premiere Pro CC 2017. First, a very late freezing moment was created by removing 5 frames (=0.17 s) from the moment the car either entered the bike path/lane in near-miss and crash situations or the moment the car stopped in the safe situation. From this point of each video clip, eight additional frames were removed four times to create four additional versions of each clip: late (=0.43 s), intermediate (=0.70 s), early (=0.97 s), and very early (=1.24 s) freezing moments (see Fig. 3.1). The time between the very late freezing moment and the conflict/collision varied between clips from 0.20 to 1.47 s (Table 3.2). After the video clip had played, the last frame was frozen. From the moment of the freeze, the relevant car was encircled for 2 s, after which the same static image without the circle remained visible for another 2 s. Clips with very late freezing moments were between 13.75 and 21.42 s long (including frozen frames). A total of 50 video clips (10 intersection situations * 5 clip freezing moment conditions) were created.

The estimated approach speeds of the cyclists differed between the 10 intersection situations, ranging from 20 km/h in Situation 1 to 42 km/h in Situation 7 (Table 3.2). These speeds are generally higher than the cruising speeds observed among conventional bicycle users (e.g., De Waard et al., 2014; Kircher et al., 2018). However, the speeds are in line with cruising speeds collected during naturalistic cycling studies among e-bike users (e.g., Rotthier et al., 2017; Stelling-Konczak et al., 2017) and with average speeds reported by users of racing bicycles (Hendriksen et al., 2008).

Table 3.2. Overview of the 10 intersection situations, estimated cycling speed, estimated time required to come to a full stop, and times between very early and very late clip freezing moments and the moment of conflict/collision. Note that the very late freezing moment was created by removing 5 frames (0.17 s) from the moment the car entered the bike path.

No.	Intersection situation	Bicycle facility	Estimated cycling speed ^a (km/h)	Estimated time to stop based on cycling speed (s)		Time between freezing moment and the conflict/collision point ^b (s)	
				Deceleration rate 3.1 m/s ²	Deceleration rate 4.6 m/s ²	Very early	Very late
1	Crash	Yes	20.4	1.83	1.23	1.57	0.50
2	Near miss	Yes	23.0	2.07	1.39	1.60	0.53
3	Near miss	Yes	29.1	2.61	1.76	1.73	0.67
4	Near miss	Yes	28.2	2.53	1.70	1.37	0.30
5	Safe	Yes	30.2	–	–	–	–
6	Crash	Yes	31.5	2.82	1.90	1.30	0.23
7	Crash	Yes	42.0	3.76	2.54	2.53	1.47
8	Crash	No	29.3	2.63	1.77	1.77	0.70
9	Near miss	Yes	30.0	2.69	1.81	1.27	0.20
10	Crash	Yes	36.3	3.26	2.19	1.77	0.70

Notes. ^a The estimated cycling speed in the video clips was calculated by measuring the distance between the position reached 2 s prior to conflict/collision point and 34–35 m before this position in Google™ Earth (see Supplementary material), and dividing this distance by the duration of the moving video clip between these two points.

^b For near-miss situations, a conflict point was defined as the moment when the car entered the cyclist's bike lane. For crash situations, a collision point was defined as the moment when the cyclist collided with the car (see Supplementary material for the video frames of these points).

Taylor (1993) computed that the maximum attainable deceleration of cyclists is 5.5m/s². However, braking tests using various types of bicycles suggest that cyclists decelerate at a somewhat lower rate of 3.5 to 4.5 m/s² (Beck, 2004). Data from a braking task (Kováčsová et al., 2016) were used to estimate the cyclists' average deceleration (3.1 m/s²) and the 90th percentile value (4.6 m/s²). Using these values, it was computed that the cyclist had insufficient time to avoid a (potential) collision by means of braking, for each of the nine 'very late' safety-critical situations (Table 3.2).

3.2.3. Survey Monkey

The online video-clip survey consisted of 14 web pages written in the English language. On the first page, participants provided their consent for participating in this study. Second, participants completed an introduction questionnaire with items on demographic characteristics, cycling, and driving experience. Weekly cycling mileage in the summertime was indicated on a 6-point scale ranging from *never* (1) to *every day* (6). As mentioned above, participants who indicated 'never' were excluded. The weekly cycling frequency in the summertime was indicated on a 10-point scale ranging from *0 km/mi* (1) to *more than 201 km (more than 125 mi)* (10).

The next 11 pages consisted of 1 practice and 10 experimental video clips and an 8-item questionnaire after each video clip. In this questionnaire, participants were asked to indicate their responses to the following items:

(1) Perceived risk ("The situation was risky.") – participants indicated their response on a 7-point Likert scale from *strongly disagree* (1) to *strongly agree* (7).

(2) Cyclist's slowing-down behavior ("Imagine that you are the cyclist in the video. Would you slow down?") – participants were asked to choose between *yes, I would slow down* and *no, I would continue cycling at this speed*.

(3) Prediction of the driver's behavior ("Imagine that the cyclist in the video will continue cycling at this speed. Will the car driver let the cyclist cross first?") – participants were asked to choose between *yes, the car driver will slow down and let the cyclist cross first* and *no*.

(4) Certainty about the driver's behavior ("I am certain about my previous answer.") – participants indicated their response on a 7-point Likert scale from *strongly disagree* (1) to *strongly agree* (7).

(5) Factors that contributed to the prediction of the driver's behavior ("Which factors contributed to your prediction?") – this was a checkbox item where participants could select from seven bottom-up cues (including the speed of the car, turn signals, and road markings) and two top-down cues (priority rules and prior experience), see Fig. 3.3, for all nine options. Participants could also report other factors in a textbox.

(6) Priority rules ("The encircled car has priority in this situation.") – participants indicated their response using the following three options: *yes, no, unsure*.

(7) Number of times the video was played ("How many times did you watch the video?") – participants indicated their response using a numerical scale ranging from *0* to *more than 5*.

(8) Color of the encircled car ("What was the color of the encircled car?") – participants could choose one of the four colors where only one option was correct (e.g., *silver, red, green, black*).

Item 7 was included to verify whether the number of video replays affected participants' prediction correctness. Item 8 was a quality control item used to select only participants who watched the video clips prior to answering the questionnaire.

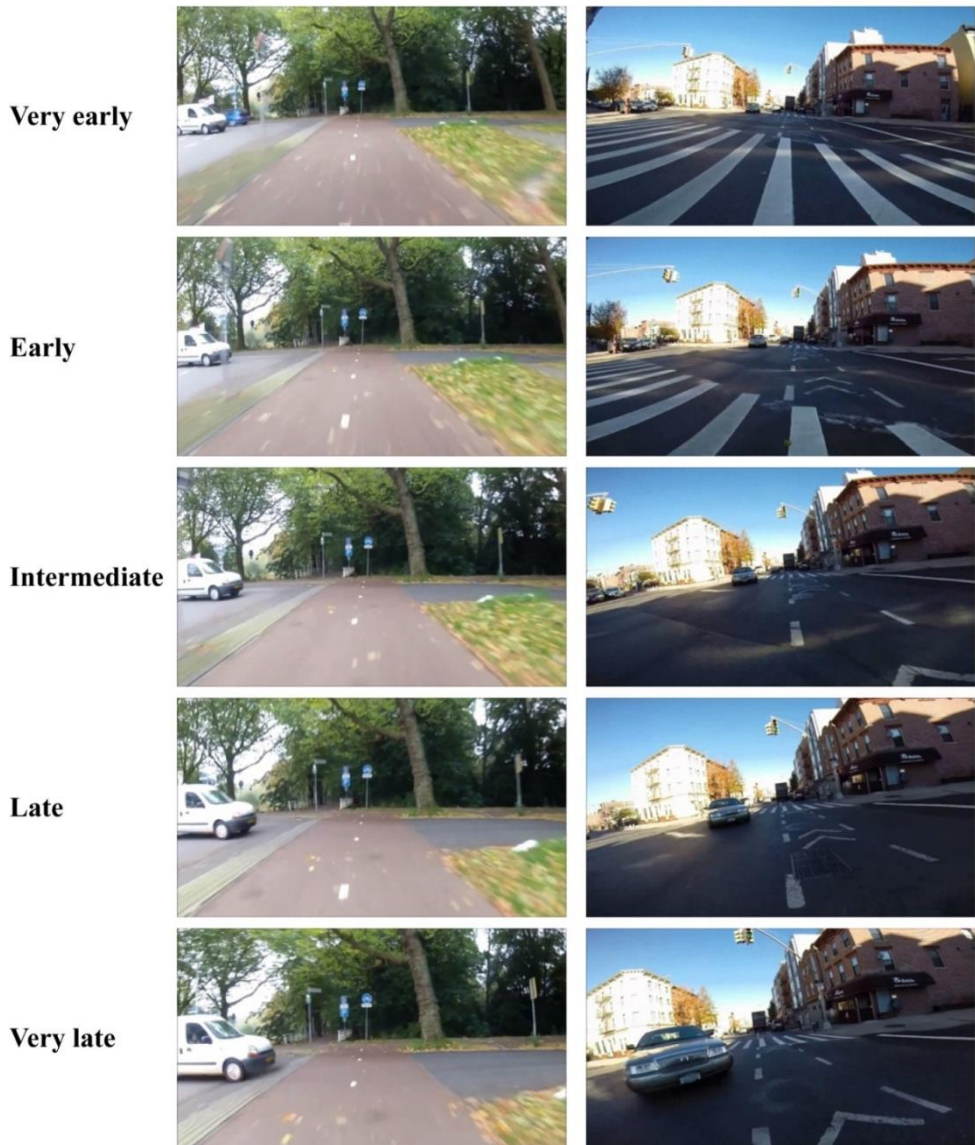


Fig. 3.1. The five freezing moments of a near-miss situation (Situation 3; left) and a crash situation (Situation 6; right). See Supplementary material for the final frames of all 10 intersection situations.

On the first of the 11 video-clip pages, participants read the instructions, watched a practice video clip, and reported their answers to the eight questions mentioned above. The task instruction was as follows: “You will now look at videos taken from a cyclist’s perspective. In each video, you will have to pay attention to a particular car. After each video, you will answer questions about a car that is encircled at the end of the video. In

each video, the cyclist is going straight ahead. When traffic lights are present in the video, the cyclist always has a green light. Please watch the videos and complete the questions in the order they appear. Please watch each video only once. In case you did not notice the car about which we ask you questions, you may replay the video once again. However, we kindly ask you to pay attention during the first viewing."

On the last questionnaire page, participants completed the Cycling Skill Inventory (CSI) and items on accident involvement during the last three years as a cyclist and as a car driver. The psychometric analysis of the CSI data has been reported elsewhere (De Winter et al., 2018).

3.2.4. Procedure

The study was of mixed between-within subjects design. The 50 experimental video clips were divided into five sets (i.e., five different forms of the SurveyMonkey online survey). Each participant was presented with 10 video clips; they saw each of the 10 intersection situations once and encountered each of the five clip freezing conditions twice. The order of the clip freezing conditions and the order of the intersection situations were counterbalanced across participants. All video clips were uploaded to YouTube and embedded into the online survey. Because of this, we could not control how many times each participant played the video clips.

Participants recruited through CrowdFlower were randomly allocated to one of the five sets. Participants recruited through Facebook were redirected to the survey via the posts with an Internet link to one of the five sets of the survey. Randomly selected Internet links to the survey were posted on the cycling-related Facebook groups based in the Netherlands (e.g., Bikes in Groningen). It took on average 20 min to complete the survey.

3.2.5. Analysis

First, a data check of responses from 1030 participants who met the eligibility and quality control criteria was performed. Participants had the option to respond I prefer to not respond to the items in the introduction and final questionnaire (i.e., background, cycling, driving-related, and accident-related items). These responses were considered as missing values in the analysis. Text responses to the other cue option were coded as "other" in case they were different from the nine predefined cues (e.g., "The driver might not be able to see the cyclist."). In some cases, participants mentioned road markings or experience in their comments while they did not select these predefined checkboxes. Therefore, these responses were edited accordingly (e.g., "Bad experience with vans being in a hurry." was coded as the "I have experience as a cyclist at a similar intersection" cue).

We first calculated participants' predictions of the car driver's behavior, self-reported slowing-down behavior, and average perceived risk levels as a function of video clip freezing moments. The remaining analyses were conducted without the safe situation, as the safe situation was included only for method validation purposes.

We proceeded with an analysis of the reported bottom-up and top-down cues. The frequencies of the reported cues were calculated for correct (i.e., the car driver will not let the cyclist cross first) and incorrect (i.e., the car driver will let the cyclist cross first) predictions of the driver's behavior. In this analysis, the percentages of reported cues were first calculated per clip freezing moment for each video clip, and then the percentages of each cue were averaged across clip freezing moment and the nine intersection situations. In addition, percentages of reported cues were plotted as a function of video clip freezing moment.

Finally, Spearman's rank-order correlations, linear regressions, and linear hierarchical regressions were conducted at the level of individual participants. Prior to these statistical analyses, participants responses on "prediction of the driver's behavior," "cyclist's slowing-down behavior," and "perceived risk" items were averaged across: (a) the four near-miss situations and clip freezing moments, and (b) the five crash situations and clip freezing moments. Similarly, the 10 cue-related responses were averaged across the five clip freezing moments of the four near-miss or the five crash intersection situations. Except for the "perceived risk" item, participants indicated their responses using binary options. The averaged scores of these binary items ranged between 0% and 100% (e.g., 0%, 25%, 50%, 75%, 100% for near-miss situations), where 100% refers to perfect accuracy in predicting the driver's behavior (i.e., a participant correctly predicted that the car would not stop in all four near-miss situations), always slowing-down, or always reporting a particular cue.

A linear regression analysis was conducted with predictions of the driver's behavior as the dependent variable and the 10 cues as predictors. Next, a hierarchical linear regression analysis was conducted with self-reported slowing-down behavior as the dependent variable. In the hierarchical regression models, background and cycling variables (i.e., gender, age, weekly cycling mileage, and cycling frequency) were entered in Step 1, prediction of the driver's behavior in Step 2, and perceived risk in Step 3. The regression analyses were conducted for near-miss and crash situations separately. As shown by Hellevik (2009), linear regression analysis can safely be used instead of logistic regression analysis. Linear and logistic regression analyses yield highly correlated regression coefficients and p-values, while an important advantage of linear regression analysis is the "intuitive meaningfulness of the linear measures as differences in probabilities" (Hellevik, 2009, p. 59).

Additionally, we analyzed cross-cultural differences in participants' predictions of the car driver's behavior, self-reported slowing-down behavior, and perceived risk in the near-miss and crash situations. Ten countries that were represented by more than 30 participants were included in this analysis. The percentages were calculated for each of the five clip freezing moments and subsequently averaged across the four near-miss or five crash situations. Due to the relatively small sample sizes per freeze frame conditions, the results should be interpreted with appropriate caution (see Supplementary material).

3.3. Results

3.3.1. Predictions of the car drivers' behaviors and participants' self-reported slowing-down behaviors

As can be seen in Fig. 3.2 (left), the percentage of participants who predicted that the car driver would not let the cyclist cross first increased as a function of elapsed time in the four near-miss situations (blue lines) and the five crash situations (black lines), and decreased in the safe situation (green line). In other words, the accuracy of participants' predictions increased with elapsed time in all 10 intersection situations, being the most accurate in the very late clip freezing moment. However, as shown in Table 3.2, for the late clip freezing moment, there was not enough time to come to a full stop. Participants' predictions of the driver's behavior were more accurate in the near-miss situations than in crash situations (Table 3.3).

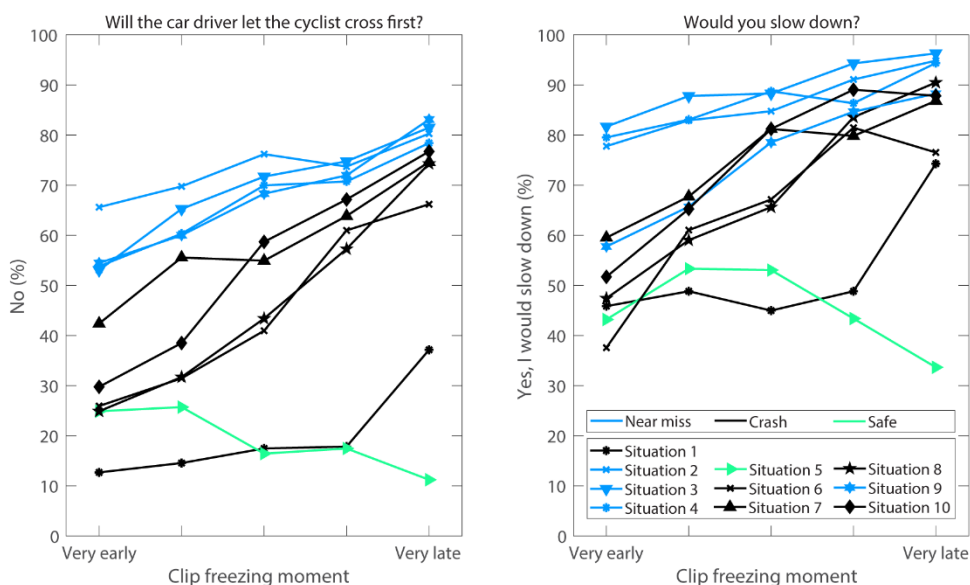


Fig. 3.2. Left: Percentage of participants who reported no to the question “Imagine that the cyclist in the video will continue cycling at this speed. Will the car driver let the cyclist cross first?” as a function of intersection situation and clip freezing moment. Right: Percentage of participants who reported yes, I would slow down to the question “Imagine that you are the cyclist in the video. Would you slow down?” as a function of intersection situation and clip freezing moment. The values of the markers are based on the responses of 189 to 213 participants.

Fig. 3.2 (right) shows that similar to the predictions of the drivers' behaviors, participants' self-reported slowing-down behaviors increased with elapsed time in the safety-critical situations (blue and black lines) and decreased with elapsed time in the

safe situation (green line). Participants reported to slow down more in the near-miss situations compared to the crash situations, especially for the early clip freezing moments (Table 3.3).

Table 3.3. Mean percentages of correct predictions of the car drivers' behavior (top), mean percentages of self-reported slowing-down behavior (center), and mean scores of perceived risk (bottom) for the three intersection situation types and the five clip freezing moments.

<i>Will the car driver let the cyclist cross first?</i>	% of No responses				
	Very early	Early	Intermediate	Late	Very late
Near miss	56.7	63.8	71.5	72.8	80.8
Crash	27.1	34.4	43.1	53.4	65.8
Safe	24.9	25.7	16.4	17.5	11.2
<i>Would you slow down?</i>	% of Yes, I would slow down responses				
	Very early	Early	Intermediate	Late	Very late
Near miss	74.2	79.9	85.1	89.1	93.4
Crash	48.4	60.4	68.0	76.5	83.2
Safe	43.2	53.3	53.1	43.4	33.7
<i>The situation was risky.</i>	Mean (1 = Strongly disagree; 7 = Strongly agree)				
	Very early	Early	Intermediate	Late	Very late
Near miss	3.71	4.16	4.33	4.73	5.07
Crash	3.45	3.89	4.45	4.94	5.61
Safe	3.08	3.46	3.66	3.62	3.26

On average, participants reported playing the video clips 1.40 times ($SD = 0.61$). There was no statistically significant correlation between the number of times the video was played and correctly predicting the car driver's behavior ($\rho = 0.02$, $p = .454$, $n = 1030$) nor with the correctness of the reported slowing-down behavior (i.e., yes, I would slow down) ($\rho = 0.01$, $p = .780$, $n = 1030$). Overall, participants were certain about their prediction of the car driver's behavior (mean = 5.33, $SD = 1.05$, on the scale from 1 to 7), and their average certainty was similar across the five clip freezing moments (5.21 in the very early to 5.58 in the very late condition). Correctly predicting the car driver's behavior was positively associated with the reported level of certainty ($\rho = 0.11$, $p < .001$, $n = 1030$).

3.3.2. Reported bottom-up and top-down cues

In the safety-critical situations (i.e., near-miss and crash), participants selected on average 1.60 cues per video clip ($SD = 0.68$). Fig. 3.3 shows that the cues concerning the car speed (cues 1–4) and priority rules (cue 8) were reported most frequently among the available options. As can be seen in Fig. 3.3, there were differences between the

reported cues for correct and incorrect predictions: participants who correctly predicted that the car would not slow down typically reported that the car's high speed (cue 1) or the car's acceleration (cue 2) contributed to their prediction. On the other hand, participants who falsely believed that the car would slow down typically reported that the car's low speed (cue 3), or car's braking (cue 4), or priority rules (cue 8) contributed to their prediction. Further, participants more frequently reported their cycling experience (cue 9) when making correct predictions. Frequently mentioned cues in the other category (cue 10) were the distance between the cyclist and the car, the car's initiation or non-initiation of the turn, the driver's looking behavior, the position of the car at the intersection (e.g., the car is halfway through the intersection), a blind spot, and the presence of other road users (e.g., pedestrian, leading car). Overall, similar results for percentages of all reported cues were found for near-miss and crash situations (Fig. 3.3).

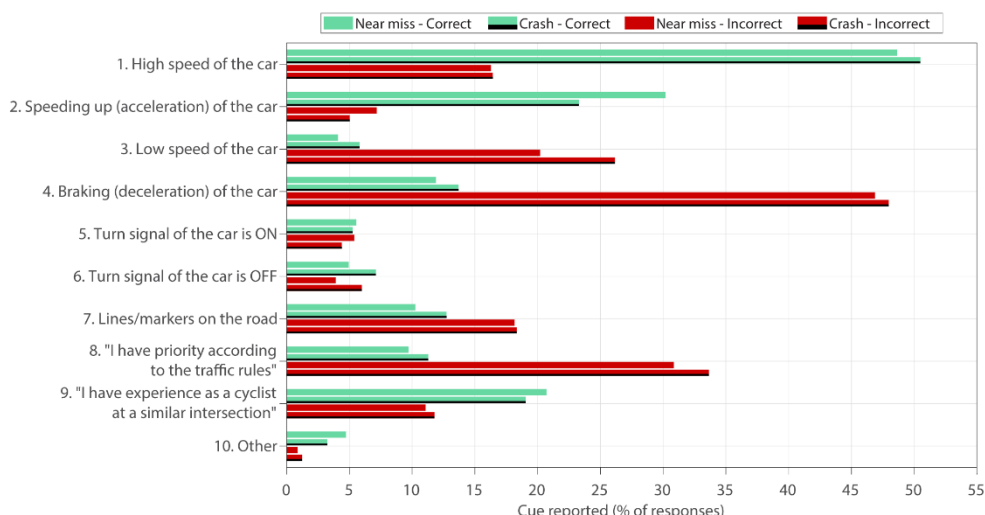


Fig. 3.3. Percentage of participants who reported bottom-up cues (cues 1–7) and top-down cues (cues 8 & 9) for correct (green) and incorrect (red) predictions of the car driver’s behavior averaged across five clip freezing moments in near-miss and crash situations. Participants indicated their responses using a checkbox item “Which factors contributed to your prediction (of the driver’s behavior)?”

An examination of the car speed cues across the five clip freezing moments (Fig. 3.4) showed that high speed and acceleration of the car (cues 1 & 2) were selected more frequently when being temporally closer to the conflict, whereas low speed and deceleration of the car (cues 3 & 4) were selected more frequently in the early clip freezing moments. The percentage of “I have priority according to the traffic rules” responses was similar across the five clip freezing moments (Fig. 3.4).

The percentages of participants who correctly reported that the car driver did not have right of way ranged between 43.0% in Situation 2 and 76.2% in Situation 5 (see

Supplementary material for the results of all 10 situations). Participants were more likely to know that the cyclist had right of way in situations where priority road markings were visible or in situations where the cyclist rode in a bike lane. However, approximately half of the participants incorrectly reported or were not aware of the priority rules in situations where the cyclist rode on a physically separated bike path (Situations 2, 3, and 4).

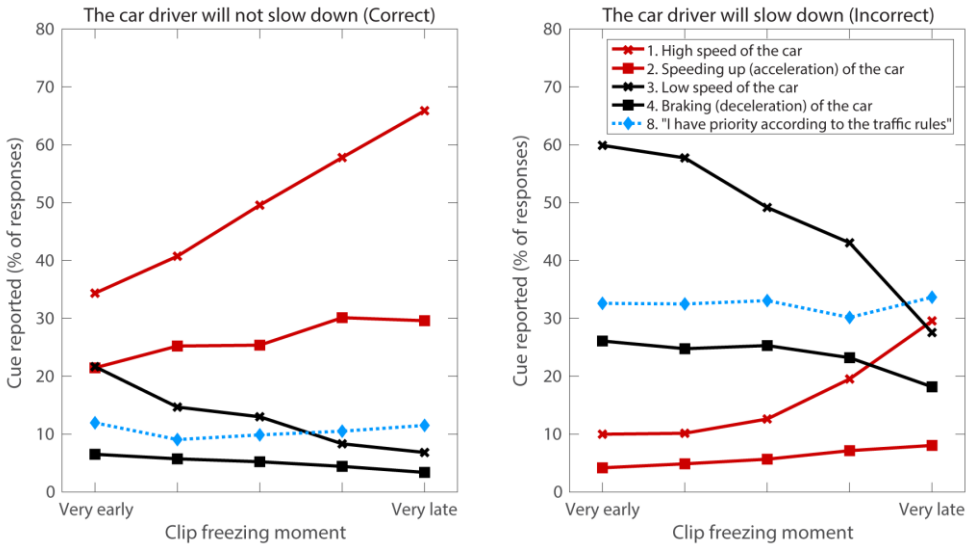


Fig. 3.4. Percentage of participants who reported a particular cue as a function of the clip freezing moment. Left: results for video clips where participants made a correct prediction about the car driver’s behavior; Right: results for video clips where participants made an incorrect prediction about the car driver’s behavior.

Table 3.4 shows linear regression analyses for participants' correct predictions of the car driver's behavior in near-miss (left) and crash (right) situations. In both models, high speed and acceleration (cues 1 & 2) as well as “I have experience as a cyclist at a similar intersection” (cue 9) and other cues (cue 10) were positively associated with making correct predictions of the driver's behavior. Low speed and deceleration (cues 3 & 4) and “I have priority according to the traffic rules” (cue 8) were negatively associated with making correct predictions of the driver's behavior, meaning that the probability that a participant made a correct prediction was lower if a participant had selected these cues. Turn signals and lines/markers on the road did not have a statistically significant relationship with the predicted driver's behavior in neither of the two models ($p > .01$). The explained variance was higher for near-miss situations ($R^2 = 0.33$) than for crash situations ($R^2 = 0.25$).

Table 3.4. Linear regression analysis for participants' correct predictions of the driver's behavior in near-miss and crash situations. Statistically significant predictors are shown in boldface.

Predictor (cue) ^a	Near-miss (4 situations)				Crash (5 situations)			
	<i>B</i>	<i>SE B</i>	β	<i>p</i>	<i>B</i>	<i>SE B</i>	β	<i>p</i>
(Constant)	62.667	2.362		<0.001	42.562	2.175		<0.001
1. High speed of the car	0.198	0.028	0.20	<0.001	0.245	0.030	0.24	<0.001
2. Speeding up (acceleration) of the car	0.278	0.030	0.25	<0.001	0.283	0.037	0.21	<0.001
3. Low speed of the car	-0.218	0.034	-0.19	<0.001	-0.151	0.030	-0.15	<0.001
4. Braking (deceleration) of the car	-0.239	0.048	-0.13	<0.001	-0.098	0.033	-0.08	0.003
5. Turn signals of the car are ON	-0.085	0.055	-0.04	0.123	0.032	0.058	0.02	0.584
6. Turn signals of the car are OFF	0.095	0.058	0.04	0.103	-0.027	0.045	-0.02	0.558
7. Lines/markers on the road	-0.011	0.036	-0.01	0.747	-0.045	0.032	-0.04	0.156
8. "I have priority according to the traffic rules"	-0.250	0.031	-0.22	<0.001	-0.167	0.025	-0.19	<0.001
9. "I have experience as a cyclist at a similar intersection"	0.168	0.028	0.16	<0.001	0.101	0.028	0.10	<0.001
10. Other	0.240	0.064	0.10	<0.001	0.185	0.077	0.07	0.016
<i>R</i> ²	0.33				0.25			
Adj. <i>R</i> ²	0.32				0.24			
<i>F</i> (<i>df1</i> , <i>df2</i>), <i>p</i>	49.97 (10, 1019), <0.001				33.27 (10, 1019), <0.001			

Notes. ^a Responses were averaged across the 4 near-miss situations, or across the 5 crash situations. The average scores per cue ranged from 0% to 100%, where 100% refers to always reporting the particular cue.

3.3.3. Factors predicting self-reported cyclists' behavior

As can be seen in Table 3.5, participants were more likely to report to slow down when they correctly predicted the driver's behavior ($\rho = 0.25$ and $\rho = 0.19$ in near-miss and crash situations, respectively) and when they perceived higher risk ($\rho = 0.27$ and $\rho = 0.32$ in near-miss and crash situations, respectively). Age was positively correlated with slowing-down ($\rho = 0.06$ and $\rho = 0.10$ in near-miss and crash situations, respectively). Correlations between cycling experience (i.e., weekly cycling mileage and cycling frequency), on the one hand, and participants' slowing-down behavior, correctly predicting the driver's behavior, and perceived risk, on the other, were all nonsignificant ($p > .01$). Finally, self-reported accident involvement as a cyclist was not significantly associated with participant's slowing-down behavior, correctly predicting the driver's behavior, or perceived risk ($p > .01$).

The results of linear hierarchical regression analyses for predicting the cyclists' self-reported slowing-down behavior are shown in Table 3.6 (near-miss situations) and Table 3.7 (crash situations). At Step 1, only age was significantly associated with slowing-down ($\beta = 0.08$ and 0.09 , for near-miss and crash situations, respectively). At Step 2, correctly predicting that the driver will not slow down contributed to the cyclists' slowing-down ($\beta = 0.25$ and 0.21 for near-miss and crash situations, respectively). At Step 3, perceived risk

also contributed significantly to cyclists' slowing-down behavior in near-miss ($\beta = 0.25$) as well as in crash situations ($\beta = 0.32$). In near-miss situations, the relationship between the prediction of the driver's behavior and cyclists' slowing-down remained essentially unchanged once perceived risk was entered into the model ($\beta = 0.23$). In crash situations, this relationship was reduced but remained statistically significant after controlling for perceived risk ($\beta = 0.15$).

Table 3.5. Spearman rank-order correlations among background variables, crash involvement, prediction of the car driver's behavior, self-reported slowing-down behavior, and perceived risk.

	1	2	3	4	5	6	7	8	9	10	11
1 Gender (1 = female, 2 = male)	–										
2 Age (years)	–0.15***	–									
3 Weekly cycling mileage ^a	0.12**	–0.06*	–								
4 Cycling frequency ^b	0.02	–0.03	0.53***	–							
5 Accident involvement (#)	0.13***	–0.18***	0.15***	0.19***	–						
6 Accident with a motor vehicle at an intersection (0 = no, 1 = yes)	0.03	–0.13***	0.07*	0.04	0.38***	–					
7 Near miss: Correctly predicting the driver's behavior ^c	–0.02	0.03	–0.04	–0.04	–0.02	0.02	–				
8 Near miss: Cyclist's slowing down ^c	0.01	0.06*	–0.05	–0.03	0.02	0.05	0.25***	–			
9 Near miss: Perceived risk ^c	0.04	0.12***	0.04	0.01	–0.05	0.01	0.08**	0.27***	–		
10 Crash: Correctly prediction the driver's behavior ^d	–0.02	–0.05	–0.03	–0.03	–0.02	0.01	0.38***	0.01	0.01	–	
11 Crash: Cyclist's slowing down ^d	0.00	0.10**	–0.05	–0.06	0.03	0.04	–0.02	0.32***	0.07*	0.19***	–
12 Crash: Perceived risk ^d	0.13***	0.01	0.01	–0.04	0.03	0.06*	0.03	0.17***	0.54***	0.18***	0.32***

Notes. ^a Weekly cycling mileage in the summertime was indicated on a 10-point scale (from 1 = 0 km/mi to 10 = more than 201 km /more than 125 mi).

^b Weekly cycling frequency in the summertime was indicated on a 6-point scale (from 1 = never to 6 = every day; participants who indicated never were excluded).

^c Responses were averaged across the 4 near-miss situations.

^d Responses were averaged across the 5 crash situations.

Samples size differed between 1,016 and 1,030 for the 66 pairs of variables listed.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.6. Linear hierarchical regression analysis for predicting cyclists' self-reported slowing-down behavior in the near-miss situations. Statistically significant predictors are depicted in boldface.

Predictor	Near-miss (4 situations)				R^2	Adj. R^2	$F(df1, df2)$	p
	B	$SE B$	β	p				
Step 1					0.01	0.00	1.89 (4, 1011)	0.110
(Constant)	78.166	4.494		<0.001				
Gender (1 = female, 2 = male)	1.323	1.471	0.03	0.369				
Age (years)	0.167	0.067	0.08	0.013				
Weekly cycling mileage ^a	-0.324	0.406	-0.03	0.426				
Cycling frequency ^b	-0.116	0.748	-0.01	0.877				
Step 2					0.07	0.06	14.69 (5, 1010)	<0.001
(Constant)	65.361	4.636		<0.001				
Gender (1 = female, 2 = male)	1.375	1.426	0.03	0.335				
Age (years)	0.160	0.065	0.08	0.014				
Weekly cycling mileage ^a	-0.204	0.394	-0.02	0.605				
Cycling frequency ^b	-0.019	0.725	0.00	0.979				
Prediction of the driver's behavior ^c	0.175	0.022	0.25	<0.001				
Step 3					0.13	0.12	24.96 (6, 1009)	<0.001
(Constant)	50.321	4.824		<0.001				
Gender (1 = female, 2 = male)	0.757	1.381	0.02	0.584				
Age (years)	0.105	0.063	0.05	0.099				
Weekly cycling mileage ^a	-0.339	0.381	-0.03	0.375				
Cycling frequency ^b	0.047	0.701	0.00	0.947				
Prediction of the driver's behavior ^c	0.161	0.021	0.23	<0.001				
Perceived risk ^d	4.368	0.518	0.25	<0.001				

Notes. ^a Weekly cycling mileage in the summertime was indicated on a 10-point scale (from 1 = 0 km/mi to 10 = more than 201 km /more than 125 mi).

^b Weekly cycling frequency in the summertime was indicated on a 6-point scale (from 1 = never to 6 = every day; participants who indicated never were excluded).

^c The scores were averaged over the four near-miss situations and expressed on a scale from 0% to 100%, where 100% refers to perfect accuracy in predicting the driver's behavior (i.e., the car driver will not let the cyclist cross first).

^d Perceived risk was indicated on a 7-point scale (from 1 = strongly disagree to 7 = strongly agree) and averaged over the four near-miss situations.

Table 3.7. Linear hierarchical regression analysis for predicting cyclists' self-reported slowing-down behavior in the crash situations. Statistically significant predictors are depicted in boldface.

Predictor	Crash (5 situations)				R^2	Adj. R^2	$F(df1, df2)$	p
	B	$SE B$	β	p				
<i>Step 1</i>					0.01	0.01	3.36 (4, 1011)	0.010
(Constant)	62.798	5.256		<0.001				
Gender (1 = female, 2 = male)	1.845	1.721	0.03	0.284				
Age (years)	0.228	0.079	0.09	0.004				
Weekly cycling mileage ^a	-0.380	0.475	-0.03	0.424				
Cycling frequency ^b	-1.129	0.875	-0.05	0.197				
<i>Step 2</i>					0.06	0.05	12.39 (5, 1010)	<0.001
(Constant)	51.421	5.395		<0.001				
Gender (1 = female, 2 = male)	2.095	1.682	0.04	0.213				
Age (years)	0.261	0.077	0.10	0.001				
Weekly cycling mileage ^a	-0.292	0.465	-0.02	0.529				
Cycling frequency ^b	-1.060	0.855	-0.04	0.215				
Prediction of the driver's behavior ^c	0.207	0.030	0.21	<0.001				
<i>Step 3</i>					0.15	0.15	30.22 (6, 1009)	<0.001
(Constant)	24.982	5.694		<0.001				
Gender (1 = female, 2 = male)	-0.443	1.614	-0.01	0.784				
Age (years)	0.239	0.073	0.10	0.001				
Weekly cycling mileage ^a	-0.461	0.441	-0.04	0.296				
Cycling frequency ^b	-0.748	0.812	-0.03	0.357				
Prediction of the driver's behavior ^c	0.147	0.029	0.15	<0.001				
Perceived risk ^d	7.480	0.705	0.32	<0.001				

Notes. ^a Weekly cycling mileage in the summertime was indicated on a 10-point scale (from 1 = 0km/mi to 10 = more than 201 km /more than 125 mi).

^b Weekly cycling frequency in the summertime was indicated on a 6-point scale (from 1 = never to 6 = every day; participants who indicated never were excluded).

^c The scores were averaged over the five crash situations and expressed on a scale from 0% to 100%, where 100% refers to perfect accuracy in predicting the driver's behavior (i.e., the car driver will not let the cyclist cross first).

^d Perceived risk was indicated on a 7-point scale (from 1– strongly disagree to 7 – strongly agree) and averaged over the five crash situations.

Lastly, as shown in Fig. 3.5, participants' perceived risk increased as a function of time in the safety-critical situations (blue and black lines). For the (very) early freezing moments, participants perceived a slightly higher risk in near-miss situations than in crash situations; the opposite effect was observed for the later three freezing moments (Table 3.3).

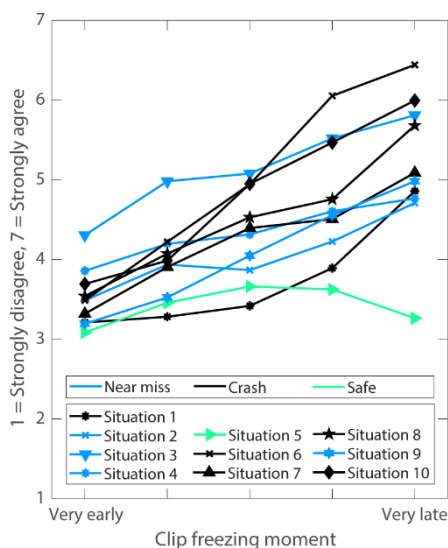


Fig. 3.5. Mean scores of perceived risk (item “The situation was risky.”) as a function of intersection situation and clip freezing moment. The values of the markers are based on the responses of 189 to 213 participants.

3.4. Discussion

The majority of bicycle–car collisions happen at intersections in urban areas (Schepers et al., 2011; Wang & Nihan, 2004). So far, crash analyses have indicated that these collisions occur even when the cyclist must have seen the approaching car (Räsänen & Summala, 1998). In the present study, we examined how cyclists' hazard anticipation develops as a function of time in safety-critical intersection situations where a car on a collision course is already detected by the cyclist. Second, we investigated which bottom-up and top-down cues guide cyclists' predictions of car drivers' right-of-way violations. Lastly, we examined how predicting that the driver will not let the cyclist cross first, perceived risk, and cycling experience contribute to the cyclists' self-reported slowing-down behavior in near-miss and crash situations.

As expected, the accuracy of cyclists' prediction of whether a car driver will let the cyclist cross first developed as a function of video clip freezing moment, with the prediction being the most accurate when the cyclist was closest to the conflict point. Although the nine safety-critical situations differed from each other in terms of location,

cyclist's approach speed, and visual features, participants showed similar patterns of correct predictions as a function of the freezing moment. Two situation-specific findings should be pointed out. First, differences in the accuracy of predicting the driver's right-of-way violation were observed between near-miss and crash situations, with overall higher accuracies in the near-miss situations. A plausible explanation for this finding is that, in near-miss situations, the car drove onto the cyclist's path relatively early; it could be therefore more obvious to the cyclist that the car driver would not let the cyclist cross first as compared to the crash situations. Second, participants showed poor accuracy in predicting the crash in Situation 1 as compared to the crashes in the other four situations. This difference can be attributed to features of the particular situation: the car driver in Situation 1 was driving slowly onto the bike path whereas drivers in the other four crash situations were driving fast while making a turn. This finding is congruent with Summala and Räsänen (2000), who observed that cyclists might interpret a low speed of a car as yielding behavior.

Participants reported various bottom-up and top-down cues when predicting drivers' behaviors. Overall, bottom-up cues were reported more often than top-down cues, suggesting that cyclists update their expectancies with perceptual features of the current situation. The most frequently reported visual bottom-up cues that contributed to the cyclists' predictions were car speed and the car's acceleration/deceleration. There appear to be two groups of cyclists, those who interpreted the car's speed as high or that the car was accelerating and those who interpreted the speed as low or that the car was decelerating. Reporting that the car drives slowly or is decelerating was associated with failing to recognize that the car driver will not let the cyclist cross first. Regarding top-down cues, participants who followed the idea that they had right of way were more likely to predict incorrectly that the car driver will yield to them, a finding which is in line with Räsänen and Summala (1998).

Cyclists reported to slow down at overall higher percentages than they reported that the car driver would not let the cyclist cross first (Fig. 3.2). This difference suggests that besides hazard anticipation, there are other factors that made the cyclists want to slow down. As safety-critical situations involve some element of risk that individuals might want to reduce (Näätänen & Summala, 1974), the subjectively perceived risk was investigated as a contributing factor to cyclists' slowing-down intentions. The results showed that a high level of perceived risk was a significant predictor of slowing-down behavior. The level of perceived risk was higher when the temporal proximity to the collision was smaller.

Cycling experience was not significantly associated with correctly predicting the driver's behavior, slowing-down, or perceived risk. Previous research showed that hazard detection skills can be improved through experience and training (e.g., Crundall et al., 2012; Horswill, 2016b), but little is known about the relationship between cycling experience and the ability to predict other road users' behaviors. It is possible that cycling experience is not a unique predictor, and that other types of experiences (e.g., driving,

walking in traffic) as well as perceptual skills (e.g., speed estimation, interception skill) are predictive of whether one is able to anticipate what a car driver will do next.

The estimated time to stop based on the cyclist's speed in the video clips showed that the cyclist would have to initiate braking at, or before, the very early clip freezing moment to avoid a collision (Situations 1, 6–8, 10). Accordingly, more than half of the participants would get involved in the crash if they braked at the moment of the freeze. Even when taking into account that participants may cycle at lower speeds than the cyclists in the video clips (for example when using conventional bicycles), cyclists might not have been able to avoid these crashes (Table 3.2). More research should be conducted to examine under which conditions cyclists have sufficient time to avoid a potential collision, preferably using objective measures of cycling behavior.

Our study has several limitations. First, the video clips were taken in real traffic, which means that we had no control over the exact timing of the events. Further, participants were not actively in control of the bicycle and they could not influence the level of risk they were willing to take by cycling slower or faster (Näätänen & Summala, 1974). On the other hand, the ecological validity of the safety-critical situations can be considered a strength of this study. Second, the selection of intersection situations was dependent on the availability of publicly available video postings. Although the situations in the video clips capture a common crash scenario where a car driver fails to give way to an oncoming cyclist, the features of the intersection environment might not be representative for all kinds of cyclists–car crashes. Third, the data collection was conducted online using self-reports. To address the main concern of online surveys that participants provide meaningless responses, stringent inclusion criteria were applied and quality control questions were included. Participants completed the survey on their own computers, as a result of which the field of view was smaller than in real cycling (see Pretto et al., 2009, showing that a small field-of-view causes an underestimation of ego-speed). Furthermore, participants had different Internet connections that could influence the quality with which the video clips were played. Lastly, there was a large variety in the participants' countries of residence but the sample sizes from each country were too small to allow us to draw conclusions on cross-cultural differences in cyclists' hazard anticipation, slowing down behavior, or perceived risk (see Supplementary material for the descriptive results).

3.5. Conclusions and recommendations

Crash analyses have shown that hazard anticipation is a contributing factor to bicycle–car collisions, but limited research exists on how cyclists anticipate drivers' right-of-way violations. Using video clips of safety-critical events, we demonstrated that cyclists' predictions of whether a car driver will yield to a cyclist or not develop as a function of time, being the most accurate temporary closest to the conflict. Participants who indicated that the car's speed or acceleration was high were more likely to correctly predict that the driver will not yield to the cyclist, whereas participants who thought that the car was driving slowly or decelerating often falsely believed that the car would let the

cyclist cross first. Furthermore, participants who reported the right-of-way rule as a contributory factor to their predictions were more likely to incorrectly predict the driver's behavior at the intersection. Lastly, this study showed that correct predictions of the driver's behavior and high perceived risk are associated with self-reported slowing-down behavior.

One recommendation would be to address these issues in cycling training programs. For example, cyclists could be taught that if one sees a car slowing-down, it does not mean that the car will stop for you. Next, taking other road users' unsafe behaviors or errors (i.e., not seeing an oncoming cyclist and making a turn) into account and performing a forgiving reaction can be addressed in the training programs as an important traffic safety principle that can prevent crashes or limit injuries (SWOV, 2010). Furthermore, the road infrastructure could be redesigned so that cars do not have to brake in a way that is confusing for cyclists. Supporting cyclists' predictions by means of warning systems may represent a promising future application. Prototypes of cooperative cyclist-car applications have already been designed (Gustafsson et al., 2013; Segata et al., 2017). Finally, it remains to be investigated to what extent the frequently reported cues contribute to cyclists' predictions in a real traffic environment, and to what extent cyclists are capable of avoiding a crash in situations where the driver has not seen the approaching cyclist.

Supplementary material

Supplementary data, analyses, and materials to this chapter are available at <http://doi.org/10.4121/uuid:b44bed89-3b9a-48fb-8758-6e2bb0d7ec72>.

References

- Allen, T. M., Lunenfeld, H., & Alexander, G. J. (1971). Driver information needs. *Highway Research Record*, 366, 102–115.
- Beck, R. F. (2004). Mountain bicycle acceleration and braking factors. *Proceedings of the Canadian Multidisciplinary Road Safety Conference XIV*, Ottawa, Ontario.
- Brown, I. D., & Groeger, J. A. (1988). Risk perception and decision taking during the transition between novice and experienced driver status. *Ergonomics*, 31, 585–597.
- Chaurand, N., & Delhomme, P. (2013). Cyclists and drivers in road interactions: A comparison of perceived crash risk. *Accident Analysis & Prevention*, 50, 1176–1184.
- Crundall, D., Chapman, P., Trawley, S., Collins, L., Van Loon, E., Andrews, B., & Underwood, G. (2012). Some hazards are more attractive than others: Drivers of varying experience respond differently to different types of hazard. *Accident Analysis & Prevention*, 45, 600–609.
- Crundall, E., Stedmon, A. W., Saikayasit, R., & Crundall, D. (2013). A simulator study investigating how motorcyclists approach side-road hazards. *Accident Analysis & Prevention*, 51, 42–50.

- Cumming, R.W. (1964). The analysis of skills in driving. *Australian Road Research*, 1, 4–14.
- De Waard, D., Lewis-Evans, B., Jelijs, B., Tucha, O., & Brookhuis, K. (2014). The effects of operating a touch screen smartphone and other common activities performed while bicycling on cycling behaviour. *Transportation Research Part F: Traffic Psychology and Behaviour*, 22, 196–206.
- De Winter, J. C. F., Kováčsová, N., & Hagenzieker, M. P. (2018). Cycling Skill Inventory: Assessment of motor-tactical and safety skills. In *Proceedings of the 7th International Cycling Safety Conference*, Barcelona: Spain.
- Deery, H. A. (1999). Hazard and risk perception among young novice drivers. *Journal of Safety Research*, 30, 225–236.
- Drury, C. G., & Pietraszewski, P. (1979). The motorists' perception of the bicyclists' hand signals. *Ergonomics*, 22, 1045–1057.
- Endsley, M. R. (1995). Toward a theory of situation awareness in dynamic systems. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 37, 32–64.
- Farrow, D., Abernethy, B., & Jackson, R. C. (2005). Probing expert anticipation with the temporal occlusion paradigm: Experimental investigations of some methodological issues. *Motor Control*, 9, 330–349.
- Gibson, J. J. (2015). *The Ecological Approach to Visual Perception: Classic Edition*. New York: Psychology Press.
- Gustafsson, P., Muñoz, J., Lindgren, L., Boda, C., & Dozza, M. (2013). BikeCOM: cooperative safety application supporting cyclists and drivers at intersections. *Proceedings of the 3rd Conference of Driver Distraction and Inattention*, Gothenburg, Sweden.
- Hellevik, O. (2009). Linear versus logistic regression when the dependent variable is a dichotomy. *Quality & Quantity*, 43, 59–74.
- Hendriksen, I., Engbers, L., Schrijver, J., Gijlswijk, R. V., Weltevreden, J., & Wiltink, J. (2008). *Elektrisch Fietsen: Marktonderzoek en verkenning toekomstmogelijkheden* [Electric bicycles: Market research and investigation] (Report KVL/B&G/2008.067). Leiden: TNO.
- Herslund, M. B., & Jørgensen, N. O. (2003). Looked-but-failed-to-see-errors in traffic. *Accident Analysis & Prevention*, 35, 885–891.
- Horswill, M. S. (2016a). Hazard perception in driving. *Current Directions in Psychological Science*, 25, 425–430.
- Horswill, M. S. (2016b). Improving fitness to drive: The case for hazard perception training. *Australian Psychologist*, 51, 173–181.
- Kircher, K., Ihlström, J., Nygårdhs, S., & Ahlstrom, C. (2018). Cyclist efficiency and its dependence on infrastructure and usual speed. *Transportation Research Part F: Traffic Psychology and Behaviour*, 54, 148–158.
- Kováčsová, N., Winter, J. C. F., Schwab, A. L., Christoph, M., Twisk, D. A. M., & Hagenzieker, M. P. (2016). Riding performance on a conventional bicycle and a

- pedelec in low speed exercises: Objective and subjective evaluation of middle-aged and older persons. *Transportation Research Part F: Traffic Psychology and Behaviour*, 42, 28–43.
- Lee, Y. M., & Sheppard, E. (2016). The effect of motion and signalling on drivers' ability to predict intentions of other road users. *Accident Analysis & Prevention*, 95, 202–208.
- Liu, C. C., Hosking, S. G., & Lenné, M. G. (2009). Hazard perception abilities of experienced and novice motorcyclists: An interactive simulator experiment. *Transportation Research Part F: Traffic Psychology and Behaviour*, 12, 325–334.
- Minsky, M. (1975). A framework for representing knowledge. In P. H. Winston (Ed.), *The Psychology of Computer Vision* (pp. 211–277). New York: McGraw–Hill.
- Møller, M., & Hels, T. (2008). Cyclists' perception of risk in roundabouts. *Accident Analysis & Prevention*, 40, 1055–1062.
- Näätänen, R., & Summala, H. (1974). A model for the role of motivational factors in drivers' decision-making. *Accident Analysis & Prevention*, 6, 243–261.
- Preto, P., Ogier, M., & Bulthoff, H. H. (2009). Influence of the size of the field of view on motion perception. *Computers & Graphics*, 33, 139–146.
- Räsänen, M., & Summala, H. (1998). Attention and expectation problems in bicycle–car collisions: An in-depth study. *Accident Analysis & Prevention*, 30, 657–666.
- Räsänen, M., & Summala, H. (2000). Car drivers' adjustments to cyclists at roundabouts. *Transportation Human Factors*, 2, 1–17.
- Rothier, B., Stevens, G., Dikomitis, L., Huyck, B., Motoasca, E., & Cappelle, J. (2017). Typical cruising speed of speed pedelecs and the link with motor power as a result of a Belgian naturalistic cycling study. *Proceedings of the 6th Annual International Cycling Safety Conference*, Davis, California, USA.
- Rumelhart, D. E. (2018). Schemata: The building blocks. In R. J. Spiro, B. C. Bruce, & W. F. Brewer (Eds.), *Theoretical Issues in Reading Comprehension: Perspectives from Cognitive Psychology, Linguistics, Artificial Intelligence and Education* (pp. 33–58). New York: Routledge.
- Schank, R. C., & Abelson, R. P. (1977). *Scripts, Plans, Goals, and Understanding: An Inquiry into Human Knowledge Structures*. Hillsdale, New Jersey: Lawrence Erlbaum Associates.
- Schepers, J. P., Kroeze, P. A., Sweers, W., & Wüst, J. C. (2011). Road factors and bicycle–motor vehicle crashes at unsignalized priority intersections. *Accident Analysis & Prevention*, 43, 853–861.
- Segata, M., Vijeikis, R., & Cigno, R. L. (2017). Communication-based collision avoidance between vulnerable road users and cars. *3rd IEEE INFOCOM Workshop on Smart Cities and Urban Computing* (SmartCity 2017), Atlanta, USA.
- Shor, R. E. (1964). Shared patterns of nonverbal normative expectations in automobile driving. *The Journal of Social Psychology*, 62, 155–163.
- Stelling-Konczak, A., Vlakveld, W. P., Wesseling, S., De Groot-Mesken, J., Christoph, M., Algera, A. J., & Twisk, D. A. M. (2017). *Speed-pedelecs op de rijbaan:*

- observatieonderzoek: Eerste praktijkonderzoek naar gedragseffecten in relatie tot veiligheid en doorstroming* [Speed pedelecs on the roadway: Observational study: First practice research into behavioural effects in relation with safety and traffic flow]. The Hague: SWOV Institute for Road Safety Research.
- Summala, H., Pasanen, E., Räsänen, M., & Sievänen, J. (1996). Bicycle accidents and drivers' visual search at left and right turns. *Accident Analysis & Prevention*, 28, 147–153.
- Summala, H., & Räsänen, M. (2000). Top-down and bottom-up processes in driver behavior at roundabouts and crossroads. *Transportation Human Factors*, 2, 29–37.
- Sun, R., Zhuang, X., Wu, C., Zhao, G., & Zhang, K. (2015). The estimation of vehicle speed and stopping distance by pedestrians crossing streets in a naturalistic traffic environment. *Transportation Research Part F: Traffic Psychology and Behaviour*, 30, 97–106.
- SWOV (2010). *Social Forgivingness* (SWOV Fact Sheet). Leidschendam: SWOV Institute for Road Safety Research.
- Taylor, D. B. (1993). Analysis of traffic signal clearance interval requirements for bicycle-automobile mixed traffic. *Transportation Research Record*, 1405, 13–20.
- Theeuwes, J. (2000). Commentary on Räsänen and Summala, “Car drivers' adjustments to cyclists at roundabouts”. *Transportation Human Factors*, 2, 19–22.
- Walker, I. (2005). Signals are informative but slow down responses when drivers meet bicyclists at road junctions. *Accident Analysis & Prevention*, 37, 1074–1085.
- Wang, Y., & Nihan, N. L. (2004). Estimating the risk of collisions between bicycles and motor vehicles at signalized intersections. *Accident Analysis & Prevention*, 36, 313–321.
- Werneke, J., Dozza, M., & Karlsson, M. (2015). Safety-critical events in everyday cycling interviews with bicyclists and video annotation of safety-critical events in a naturalistic cycling study. *Transportation Research Part F: Traffic Psychology and Behaviour*, 35, 199–212.
- Westerhuis, F., & De Waard, D. (2017). Reading cyclist intentions: Can a lead cyclist's behavior be predicted? *Accident Analysis & Prevention*, 105, 146–155.

CHAPTER 4

EMERGENCY BRAKING AT INTERSECTIONS: A MOTION-BASE MOTORCYCLE SIMULATOR STUDY

Powered two-wheeler riders are frequently involved in crashes at intersections because an approaching car driver fails to give right of way. This simulator study aimed to investigate how riders perform an emergency braking maneuver in response to an oncoming car and, second, whether longitudinal motion cues provided by a motion platform influence riders' braking performance. Twelve riders approached a four-way intersection at the same time as an oncoming car. We manipulated the car's direction of travel, speed profile, and its indicator light. The results showed that the more dangerous the situation (safe, near-miss, impending-crash), the more likely riders were to initiate braking. Although riders braked in the majority of trials when the car crossed their path, they were often unsuccessful in avoiding a collision with the car. No statistically significant differences were found in riders' initiation of braking and braking style between the motion and no-motion simulator configurations.

Kovácsová, N.¹, Grottoli, M.¹, Celiberti, F., Lemmens, Y., Happee, R., Hagenzieker, M. P., & De Winter, J. C. F. (2020). Emergency braking at intersections: A motion-base motorcycle simulator study. *Applied Ergonomics*, 82, 102970.

¹Joint first authors

4.1. Introduction

Because of their ability to maneuver on congested roads, powered two-wheelers (PTWs) are an efficient mode of transport, especially in dense urban areas. Accident analyses have shown that a common type of collision involving a PTW in an urban environment is a situation where a car drives into the path of the PTW rider at an intersection (Clarke et al., 2007; MAIDS, 2009). Although it is the car driver who violates the formal rules (Pai, 2011), the PTW rider may have been able to prevent the crash by performing an appropriate evasive maneuver. As pointed out by Crundall et al. (2013), the majority of studies on these right-of-way crashes have been concerned with the behavior of car drivers, and little empirical evidence exists concerning the behavior of riders.

An in-depth study of human errors in PTW-car crashes showed that riders often fail to perceive and anticipate the car driver's intentions and also fail to perform a satisfactory braking maneuver (Penumaka et al., 2014). Various photo- or video-based studies have been performed to study road users' ability to predict the intentions of car drivers, motorcyclists, and cyclists (e.g., Drury & Pietraszewski, 1979; Lee & Sheppard, 2016; Walker, 2005; Walker & Brosnan, 2007; Westerhuis & De Waard, 2017). For example, Lee and Sheppard (2016) found that participants were more accurate in judging turning maneuvers when a vehicle was indicating the turn compared to a condition when the vehicle's indicator was off. Furthermore, it was found that participants viewing video clips were able to judge whether the vehicle would turn even when an invalid turn signal was provided.

Previous studies on PTW rider's braking performance have relied on test-track experiments in which riders had to brake in response to discrete or artificial stimuli such as lights, road markings, or barricades (e.g., Davoodi & Hamid, 2013; Davoodi et al., 2012; Ecker et al., 2001a; Ecker et al., 2001b; Vavryn & Winkelbauer, 2004). These studies showed that the average braking distance to an unexpected object (i.e., a barricade) when traveling at a speed of 60 km/h was approximately 52 m (Davoodi & Hamid, 2013), and that response times ranged between 0.55 and 2.55 s (Davoodi et al., 2012). Similarly, a literature review about car driver's brake response times showed that the majority of studies used simple acoustic or visual stimuli rather than more naturally evolving traffic situations (Green, 2000).

Several researchers have experimentally evaluated how riders respond to right-of-way violations of car drivers. Huertas-Leyva et al. (2017) investigated riders' braking behavior in response to an approaching car at a mock three-way intersection. The results showed large individual differences in mean deceleration during emergency braking (between 3.5 m/s² and 7.6 m/s²), and an effect of the car's turn indicator, where deceleration values were lower when the indicator was on compared to when it was off, possibly because braking started earlier. Crundall et al. (2013) used a motorcycle simulator in a no-motion configuration to investigate how riders of different experience levels approached a three-way intersection when a car pulled out from a side road. The riders who had participated in an advanced riding training showed safer performance in

terms of anticipatory slowing down before the intersection compared to regular and novice riders.

Simulators have proved to be a valuable instrument for measuring hazard anticipation skills in ethically challenging emergency events (Underwood et al., 2011). However, achieving realistic braking performance in simulators remains a challenge (Boer et al., 2001; Boer et al., 2000; Jamson & Smith, 2003). Furthermore, it is technologically challenging to implement independently working front and rear brakes on PTW simulators (Stedmon et al., 2009) as well as to simulate realistic motorcycle behavior at low speeds at which the motorcycle is unstable. Despite these technological challenges, simulators are attractive tools for studying rider behavior, as simulators offer the possibility of exposing participants to critical situations without physically at risk (Carsten & Jamson, 2011; De Winter et al., 2012).

The purpose of this study was twofold: (1) to understand how PTW riders brake at an intersection when encountering a car that might violate the formal right-of-way traffic rule, and (2) to compare how no-motion and motion configurations of the simulator affect rider's braking performance. This study addressed the following two research question:

1. How do riders brake in impending-crash, near-miss, and safe intersection situations?

A rider can use the car's speed, distance to the intersection, and additional cues such as the car's indicator and car's heading to anticipate the intention of the car driver (Lee and Sheppard, 2016; Wilde, 1976). In line with Huertas-Leyva et al. (2017) and Lee and Sheppard (2016), we expected that the turn indicator light would contribute to earlier braking as compared to when the car does not use its indicator light. Further, we expected that PTW riders would initiate braking earlier when the car is approaching from the right because this car can be seen to be on a collision course with the rider. If the car is approaching an intersection from the opposite direction, the PTW rider would typically not brake unless the car initiates a left turn and starts to cross the rider's path.

2. Do longitudinal motion cues provided by a motion platform influence riders' braking performance?

We expected that there would be no significant differences in the timing of emergency braking action between no-motion and motion because no motion cues are provided to the rider when riding straight at a constant speed in the motion configuration. Based on previous research in driving simulators (e.g., Siegler et al., 2001), we expected that riders would adopt a lower deceleration (i.e., less braking) in the motion configuration than in the no-motion configuration.

4.2. Method

4.2.1. Participants

Nine motorcycle riders (license A) and four moped riders (license AM) were recruited from the employees of Siemens PLM Software, Belgium. One motorcycle rider withdrew from the experiment during the practice session due to simulator sickness. Three other

participants partially completed the experiment due to simulator sickness (see Section 4.3).

The mean age of the remaining 12 participants (10 males, 2 females) was 32.9 years ($SD = 6.1$). Participants had held their PTW license on average for 10.9 years ($SD = 5.8$) and their driving license on average for 13.1 years ($SD = 5.6$), see Table 4.1 for an overview of participants' riding experience. The study was approved by the TU Delft Ethics Committee (Ethics application no. 176, 2017).

Table 4.1. Riding experience in the last 12 months.

Riding frequency	Never	Less than once a month	Once a month to once a week	1–3 days a week	4–6 days a week
Number of participants	2	4	2	2	2
Yearly kilometers	0	1–500	501–1,000	1,001–5,000	10,001–20,000
Number of participants	2	4	3	2	1

4.2.2. Apparatus

4.2.2.1. MOTORIST riding simulator

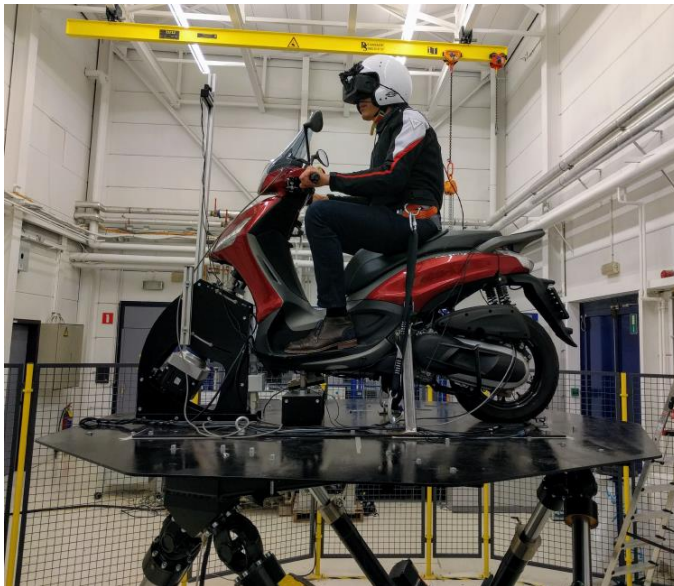


Fig. 4.1. The MOTORIST simulator with a rider wearing an Oculus Rift and safety equipment.

The experiment was conducted on the 'MOTORIST' motion-base riding simulator. The simulator consisted of a motorcycle mock-up, type Piaggio Beverly 350 cc, mounted on a MOOG motion platform (Fig. 4.1). The rider could interact with the motorcycle using the throttle handle and two brake levers. The front and rear brake levers worked

independently from each other. The rider's braking action was measured by reading the brake lever angles using an encoder. The brake lever angle was sent to a model of the hydraulic braking system, which computed the virtual braking torque applied to the wheels to slow down the simulated vehicle. The rider's steering input did not affect the virtual motorcycle in this experiment. An overview of the simulator is provided by Celiberti et al. (2016).

For safety reasons, participants had to wear a helmet and a protective jacket while riding the simulator. The helmet and jacket were also used to enhance the fidelity regarding the feeling of riding a motorcycle. Furthermore, a full-body safety harness was used to secure the participant to the motorcycle's frame.

4.2.2.2. Head-mounted display

The virtual environment was shown to participants using a head-mounted display 'Oculus Rift Developer Kit 2' (SDK 0.4) at a rate of 30 frames per second. The binocular setting of Oculus providing stereo vision was used with an inter-pupillary distance of 64 mm. The urban virtual environment was modeled using the PreScan simulation software. A speedometer was presented at the bottom of the displayed image.

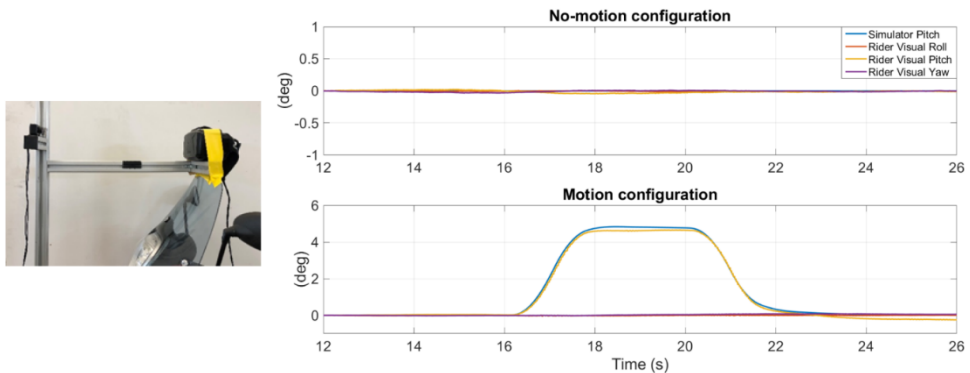


Fig. 4.2. Left: Support used to fix the Oculus with respect to the tracking camera. Right: The visual orientation computed with the Oculus Rift SDK remains constant during a no-motion configuration, whereas the visual orientation is affected by the simulator motion. The introduced pitch angle in the visualization follows the angle of the motion system as if the rider would be looking downward/upward during braking/accelerating maneuvers.

The head-mounted display was mounted on a helmet, and the external camera was mounted on a pole attached to the platform in front of the motorcycle mock-up (Fig. 4.1). This external camera tracked the headset position and was used in conjunction with an inertial measurement unit in the headset to create a visual field that takes head motion into account (Oculus, 2014). Ideally, the visual image is not affected by the motion of the

platform, and the visual orientation remains the same in both the no-motion and motion simulator configurations. The Oculus Rift uses sensor fusion to combine the data measured by the tracking camera and the inertial unit embedded in the Oculus. Even though the camera was fixed with respect to the motion system of the simulator, the measurement of the inertial unit affected the orientation of the rider view. This effect has been measured by fixing the Oculus with respect to the camera while moving the simulator as in the real experiment (Fig. 4.2 left). The results (Fig. 4.2 right) showed that, in the motion configuration, the visual orientation computed with the sensor fusion algorithm of the Oculus Rift is following the simulator's physical angle, introducing a visual pitch as if the rider would be looking downward/upward during braking/accelerating maneuvers. This effect does not occur for the no-motion configuration.

4.2.2.3. Riding configurations

In the motion configuration, the motorcycle model provided feedback to the motion base. A traditional washout motion filter was applied using pitch (forward rotation) to simulate sustained acceleration (see Supplementary material for the motion filter parameters). The motion reference point (also called 'center of rotation') was located approximately at the position of the rider's head. In the no-motion configuration, no motion cues were provided by the motion platform. Head rotation was possible around three axes in both simulator configurations.

4.2.3. Stimuli

The simulated urban environment consisted of a two-lane straight road, where after approximately 295 m, the rider arrived at a four-way intersection at which a car was always encountered. The speed limit was 50 km/h, and a priority sign was placed before the intersection. The lane width was 3.5 m, and 3 m wide sidewalks were present on both sides of the road. Small visual obstructions were present in the form of trees before the intersection. The same urban virtual environment was used for the practice and experimental sessions, see Fig. 4.3 for a top view of the intersection.

Three independent variables were manipulated to create nine different intersection situations:

- 1) *Car's direction of travel.* The car could approach the intersection:
 - a) *from the opposite direction on the main road ('From opposite'),* or
 - b) *from the right side road ('From right').*
- 2) *Car's motion.* The speed profile of the car and car's heading were programmed to create three intersection encounters (see Fig. 4.4 left). This variable was crossed with the car's direction of travel variable, resulting in six intersection situations.
 - a) *The car continues straight ('Straight').* The car was triggered at a speed of 40 km/h, and it did not decelerate. This was a safe situation if the car approached from the opposite direction, and an impending-crash situation

- if the car approached from the right. A crash would occur unless the participant braked hard.
- b) *The car begins a left turn and stops ('Stops')*. The car was triggered at a speed of 40 km/h, and it decelerated to 0 km/h. This was a near-miss for both directions of travel of the car, as the car came to a stop just before making the turn.
 - c) *The car turns left ('Turns')*. The car was triggered at a speed of 40 km/h, and it decelerated to 20 km/h before making the turn. This was an impending-crash situation for both directions of travel of the car. In case the car came from the opposite direction of the main road, a crash would occur unless the participant braked hard.
- 3) *Car's indicator*. Due to low visibility of the actual indicator light in the virtual world, the left headlight was used as an indicator only in the three 'car from the opposite direction' situations creating three additional intersection situations (see Fig. 4.4 right, situation 'From opposite, Stops (I)'). The indicator was either
- a) *on (abbreviated I)*, or
 - b) *off*.

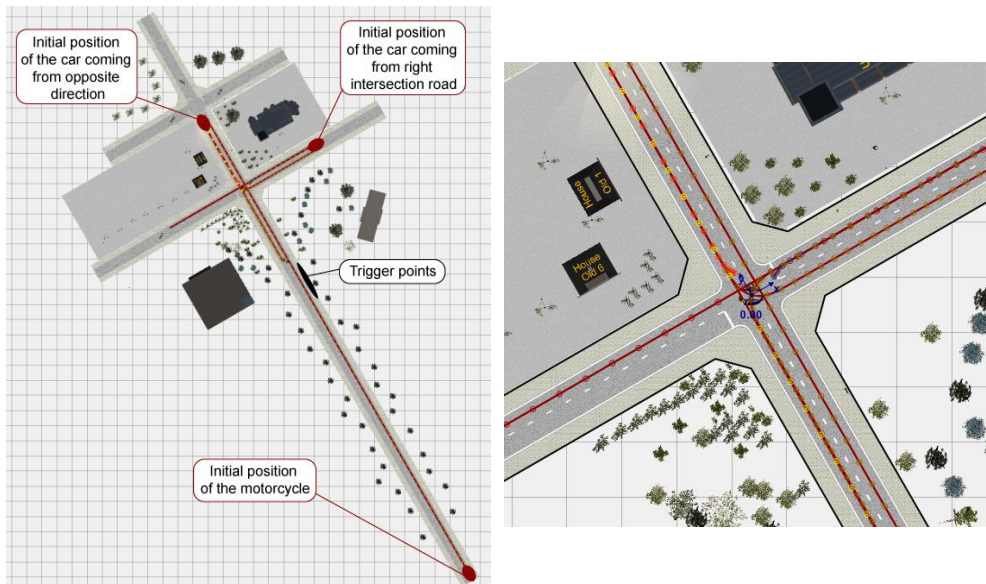


Fig. 4.3. Left: Top view of the simulated world. The trajectories of the car and motorcycle are depicted as red lines on the road. Right: Zoomed-in view. The differently colored circular markers (yellow, red, light brown, dark brown) distinguish the different trajectories of the car. The motorcycle approached from the south and always drove in the center of the right lane.

The cars were triggered when the rider was at a certain distance from the intersection (see Fig. 4.4 left for trigger points). The car behaved in a pre-programmed manner and did not adjust its behavior to the participant's motorcycle in any way. If a participant collided with the car, the simulation continued, and the participant did not receive any collision feedback. The simulation of each intersection situation stopped either approximately 50 m after the intersection or when a participant came to a stop. At the end of each intersection situation, the rider was placed back in the initial position.

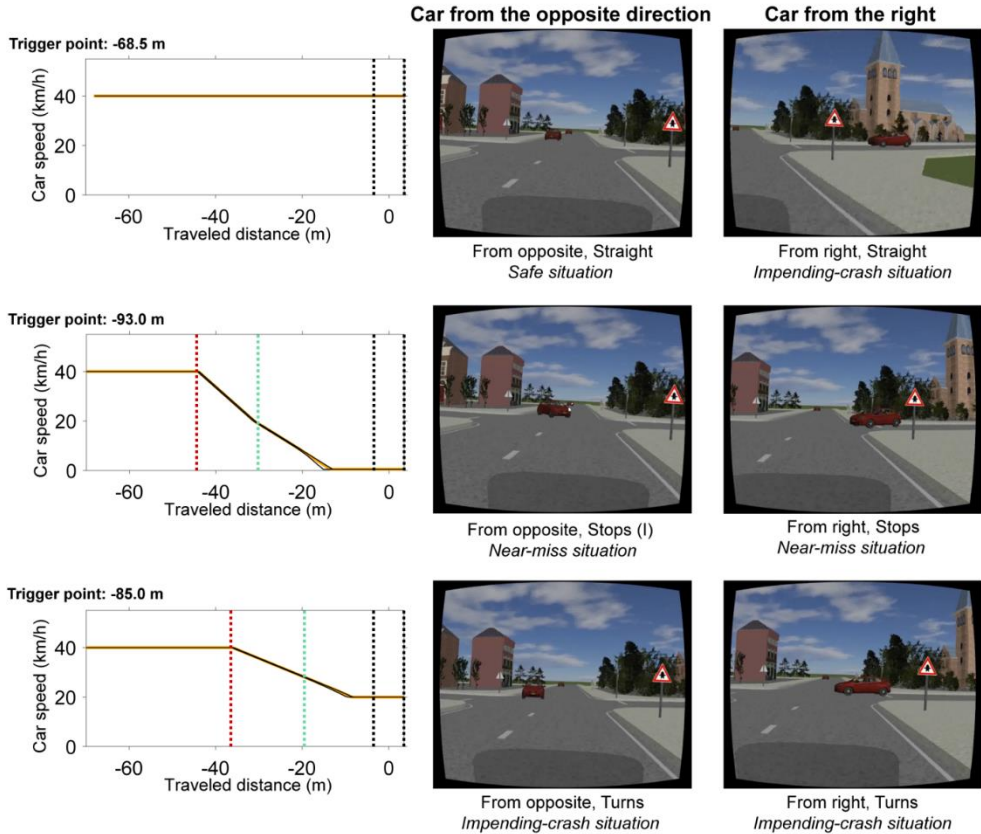


Fig. 4.4. Left: Car speed profiles and trigger points (distance between the motorcycle and the center of the intersection when the car was spawned). The black vertical lines indicate the start and end of the intersection, the red vertical line indicates the moment the approaching car started to decelerate, and the green vertical line indicates the moment when the heading of the approaching car started to change. Right: Screenshots of six intersection situations as observed by the participant. The speedometer (which was presented at the bottom of the displayed images) is not included in these screenshots.

4.2.4. Procedure

The experiment was conducted at the Siemens PLM Software facilities, Belgium. Before the simulator sessions, a consent form was signed, and the participants completed an intake questionnaire. The intake questionnaire consisted of items on demographic characteristics, riding and driving experience, and a baseline questionnaire on simulator sickness. See Fig. 4.5 for the experimental timeline.

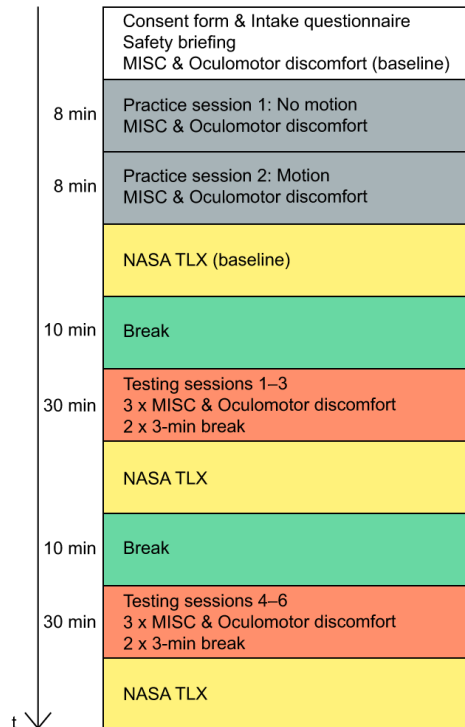


Fig. 4.5. The experimental timeline. The orange blocks consisted of either three no-motion or three motion configuration sessions and were counterbalanced across participants.

Participants conducted two practice sessions to familiarize themselves with the simulator controls, visual stimuli (e.g., triggered cars), and the emergency braking task. Riders were informed about the nine intersection situations in the consent form, and they experienced them during the practice sessions. Each practice session consisted of nine different intersection situations presented in random order. The first practice session was conducted in the no-motion configuration and the second practice session in the motion configuration.

Following the two practice sessions, a participant completed 54 different repetitions of the intersection situations (9 intersection situations x 3 repetitions x 2 simulator

configurations), divided into six sessions. Similar to the practice sessions, each testing session consisted of nine different intersection situations presented in random order and lasted approximately 8 min. Two blocks of three no-motion and three motion configuration sessions were created and counterbalanced across participants.

At the beginning of each trial, the participant was asked to hold the throttle to indicate that the simulation could start. The motorcycle automatically accelerated to 50 km/h, and this speed was maintained using cruise control until the rider started to brake. The throttle position did not influence the simulation when the motorcycle was already moving. When the rider started to brake and did not come to a full stop, the PTW automatically accelerated back to 50 km/h if the brake was fully released. Participants' task was: "You will be riding 50 km/h, try to keep this speed as long as you can and brake only when needed to avoid a crash".

After each session, simulator sickness was measured using the Misery Scale (MISC; Bos et al., 2005) and by the item on experienced oculomotor discomfort from the Simulator Sickness Questionnaire (Kennedy et al., 1993). The NASA Task Load Index (NASA TLX; Hart & Staveland, 1988) was administered three times during the experiment; once after the practice sessions, and twice after the no-motion and motion blocks. The entire experiment took approximately 2 h per participant.

4.2.5. Measures

4.2.5.1. Riding performance measures

The braking signal was averaged across the front and rear brake levers, in order to obtain an index of total braking input, where 100% represents the maximum value possible (occurring when braking 100% at the front and at the rear). A threshold of 3% of the average brake signal was used to distinguish braking from non-braking. The following measures were calculated as an average across available trials per intersection situation per person.

Brake initiation moment (m). This measure describes the moment of braking, expressed as the participant's distance to the center of the intersection at the moment the participant pressed the brakes. We used distance (m) instead of elapsed time (s) for the sake of interpretability regarding situational events such as trigger points of the car. However, it is noted that distance can readily be converted to time because the participant's motorcycle had a constant approach speed of 50 km/h. This measure was calculated for a traveled distance between 70 m before the intersection and the entrance to the intersection located 3.5 m before the center of the intersection.

Minimum riding speed (km/h). This measure describes the minimum riding speed while approaching the intersection (i.e., before a potential collision with the car). This measure was calculated for the same travel distance as the previous measure. Speed data were logged until approximately 2 km/h, after which a trial ended.

Maximum brake position (%). The maximum brake position was used as an index of how hard riders decelerated. This measure is the maximum percentage of the rider's

braking. This measure was calculated for a distance between -70 m and -3.5 m before the center of the intersection.

Brake rise distance (m). This measure represents the rider's braking style. It describes the traveled distance between the initiation of braking (threshold at 3%, as above) to the maximum brake position before the rider entered an intersection.

Percentage of trials with a stop (%). This measure indicates whether the rider came to a stop before entering the intersection. This measure was calculated for each of the four impending-crash intersection situations separately. We used a threshold of 5 km/h to distinguish stopping from not stopping.

Percentage of trials with a crash (%). The crash percentage was calculated using the distance between the centers of two vehicles in the virtual world. If this distance was below 2.4 m, a crash was recorded. The percentage of crashes was calculated for the four impending-crash intersection situations.

4.2.5.2. Self-reports

Simulator sickness (0–10). The 11-point MISC (Bos et al., 2005) and an item on oculomotor discomfort "*I experience oculomotor discomfort at the moment (eyestrain, difficulty focusing, blurred vision or headache)*." (Kennedy et al., 1993) were provided to participants to monitor the development of simulator sickness during the experiment. The MISC ranges from *no problems* (0) to *vomiting* (10). The experienced oculomotor discomfort was rated on a scale from *not at all* (0) to *very much* (10). If the participant reported a score of 6 or higher on one of these items, the experiment was interrupted, and either a longer break was taken by the participant or the participant withdrew from the experiment.

NASA TLX (1–21). The six-item NASA TLX questionnaire was used to assess riders' workload. The questionnaire contained items on mental demand, physical demand, temporal demand, performance, effort, and frustration (Hart & Staveland, 1988). Items were rated on the 21-point scale ranging from *very low* (1) to *very high* (21) and *failure* (1) to *perfect* (21) for the performance item.

4.3. Results

One female and one male participant withdrew from the motion test sessions because of experiencing severe nausea and medium oculomotor discomfort during the first motion test session. The female participant had completed two no-motion sessions, and the male participant had completed all three no-motion sessions without experiencing severe discomfort. Therefore, these two participants were included in the analysis for the no-motion configuration only. Another female participant experienced severe nausea and severe oculomotor discomfort during the last motion test session. This participant was included in the analysis for both the no-motion and motion conditions; only data from the last (sixth) session were excluded. Further, a data quality check revealed that there was a data logging error in the last no-motion session for one participant and in one motion

trial for another participant. Results reported below are based on 306 trials completed in the no-motion configuration and 260 trials completed in the motion configuration.

4.3.1. Self-reported simulator sickness and experienced workload

There were no significant differences in experienced motion sickness and oculomotor discomfort between the two simulator configurations among ten participants who completed trials for both configurations (Table 4.2). The self-reported mental demand, physical demand, and effort were significantly higher for the motion condition as compared to the no-motion condition.

Table 4.2. Minima, maxima, means, standard deviations, and results of paired sample *t*-tests for self-reported simulator sickness and NASA TLX per simulator configuration for the 10 participants who completed both simulator motion configurations.

	No motion			Motion			No motion vs. motion	
	Min	Max	Mean (SD)	Min	Max	Mean (SD)	<i>t</i> (df)	<i>p</i>
Sickness (0–10) ^a	0	4.33	1.00 (1.40)	0	4.67	1.47 (1.90)	-1.26 (9)	0.240
Oculomotor discomfort (0–10) ^a	0	5.00	1.50 (1.86)	0	5.00	1.77 (1.87)	-1.10 (9)	0.299
NASA TLX: Mental demand (1–21) ^b	3	7	4.40 (1.43)	3	11	5.90 (2.96)	-2.29 (9)	0.048
NASA TLX: Physical demand (1–21) ^b	1	12	4.90 (3.03)	3	20	8.50 (5.84)	-2.66 (9)	0.026
NASA TLX: Temporal demand (1–21) ^b	3	12	5.30 (2.71)	3	14	6.30 (3.62)	-2.24 (9)	0.052
NASA TLX: Performance (1–21) ^b	5	17	10.80 (4.21)	6	17	11.60 (3.89)	-1.31 (9)	0.223
NASA TLX: Effort (1–21) ^b	3	15	8.20 (3.99)	3	16	9.90 (5.04)	-2.85 (9)	0.019
NASA TLX: Frustration (1–21) ^b	1	14	5.10 (4.33)	1	16	4.80 (4.66)	0.90 (9)	0.394

Notes. *p* values < 0.05 are in boldface.

^a asked after each session, ^b asked after each block, i.e., three sessions.

4.3.2. Effect of visual stimuli on riders' speed and braking performance

Riders initiated braking in 16.7% of the 126 safe situation trials in which the car from the opposite direction drove straight ahead, in 50.5% out of 188 near-miss trials where the car performed an emergency stop, and in 98.0% out of 252 impending-crash trials in which the car drove into the path of the rider.

Fig. 4.6 shows that the riders did not brake immediately after the car approaching from the opposite direction started to decelerate (top and middle rows). Instead, the riders started to initiate braking right after the car started to change its heading. On average, riders initiated braking further from the intersection in 'car stops' situations as compared to the 'car turns' situations (Table 4.3).

Table 4.3. Means and standard deviations of the brake initiation moment, maximum brake position, and brake rise distance for nine intersection situations.

	Brake initiation moment (m)				Minimum riding speed (km/h)				Maximum brake position (%)				Brake rise distance (m)			
	No motion		Motion		No motion		Motion		No motion		Motion		No motion		Motion	
	Mean (SD)	n	Mean (SD)	n	Mean (SD)	n	Mean (SD)	n	Mean (SD)	n	Mean (SD)	n	Mean (SD)	n	Mean (SD)	n
From opposite, Stops ^{nm}	-25.19 (1.98)	9	-25.75 (3.45)	8	34.48 (17.06)	12	33.71 (20.34)	10	36.91 (28.50)	12	33.82 (32.72)	10	6.97 (2.67)	9	4.49 (2.55)	8
From opposite, Turns ^{lc}	-17.80 (5.28)	12	-17.94 (4.31)	10	24.31 (10.01)	12	25.27 (7.83)	10	78.91 (15.26)	12	77.39 (16.00)	10	9.26 (5.37)	12	9.33 (5.86)	10
From opposite, Straight ^s	-18.87 (7.32)	2	-23.95 (3.89)	2	50.02 (0.97)	12	50.23 (0.50)	10	1.61 (3.83)	12	0.73 (1.32)	10	6.45 (1.48)	2	4.50 (1.13)	2
From opposite, Stops (l) ^{nm}	-30.24 (11.24)	9	-28.58 (10.31)	7	34.47 (18.69)	12	33.05 (19.66)	10	31.89 (30.20)	12	30.47 (33.23)	10	9.37 (6.59)	9	7.44 (5.70)	7
From opposite, Turns (l) ^{lc}	-18.45 (5.59)	12	-21.59 (10.70)	10	23.81 (12.03)	12	21.57 (10.01)	10	78.07 (15.99)	12	75.61 (16.26)	10	8.81 (4.92)	12	11.44 (8.31)	10
From opposite, Straight (l) ^s	-29.83 (6.56)	4	-24.44 (11.08)	4	45.50 (13.22)	12	48.10 (4.54)	10	8.00 (16.98)	12	7.15 (11.19)	10	8.84 (7.42)	4	6.58 (6.50)	4
From right, Stops ^{nm}	-33.51 (6.90)	5	-39.50 (4.28)	4	46.20 (9.71)	12	43.55 (12.44)	10	8.32 (17.36)	12	10.39 (18.90)	10	6.26 (3.17)	5	12.90 (8.26)	4
From right, Turns ^{lc}	-26.83 (5.65)	11	-27.60 (7.07)	10	17.23 (14.02)	12	10.92 (8.50)	10	61.00 (25.59)	12	70.19 (21.26)	10	12.22 (5.85)	11	12.57 (9.54)	10
From right, Straight ^{lc}	-19.37 (7.31)	12	-20.15 (9.99)	10	20.39 (14.08)	12	22.89 (17.00)	10	77.14 (16.95)	12	73.98 (19.99)	10	10.19 (4.82)	12	10.66 (6.20)	10

Notes. ' (l)' the car was indicating a turn, ' s' safe situation, ' nm' near-miss situation, ' lc' impending-crash situation.

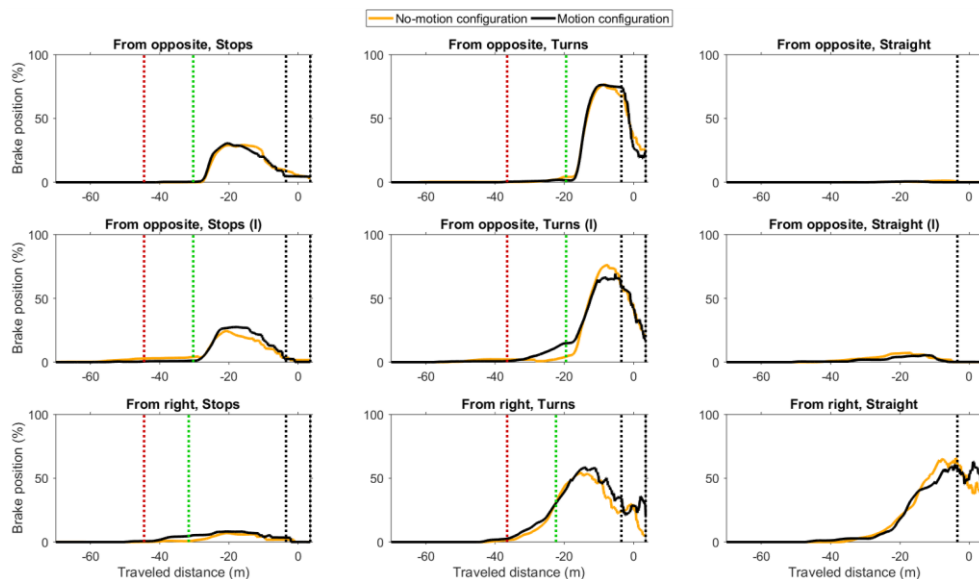


Fig. 4.6. Mean brake position (front and rear brake averaged) during the nine intersection situations per simulator motion configuration. In case a participant came to a stop, data are not shown further. The black vertical lines indicate the start and end of the intersection, the red vertical line indicates the moment when the approaching car started to decelerate, and the green vertical line indicates the moment when the heading of the approaching car started to change.

4.3.2.1. Car's indicator

Riders initiated braking on average 3.94 m (in 'Stops' situations) and 2.15 m (in 'Turns' situations) earlier when the car from the opposite direction indicated the turn as compared to when the car did not (Table 4.3). The average riding speed while approaching the intersection was similar for both indicator conditions (Fig. 4.7).

The effect of the indicator on the brake initiation moment was not statistically significant for the 'car turns' situations ($t(11) = 0.50$, $p = 0.627$ and $t(9) = 1.50$, $p = 0.169$ for the no-motion and motion configurations, respectively). The effect of the indicator on the minimum riding speed in the 'car turns' situations was not significant either ($t(11) = 0.27$, $p = 0.791$ and $t(9) = 0.93$, $p = 0.377$ for the no-motion and motion configurations, respectively). The t -tests were not conducted for the 'car stops' situations due to the low number of braking events.

Although riders braked in the 'car turns' situations, they still often crashed into the car (Table 4.4). The percentage of crash involvement was slightly lower in situations when the car indicated a turn compared to situations when the car did not indicate the turn.

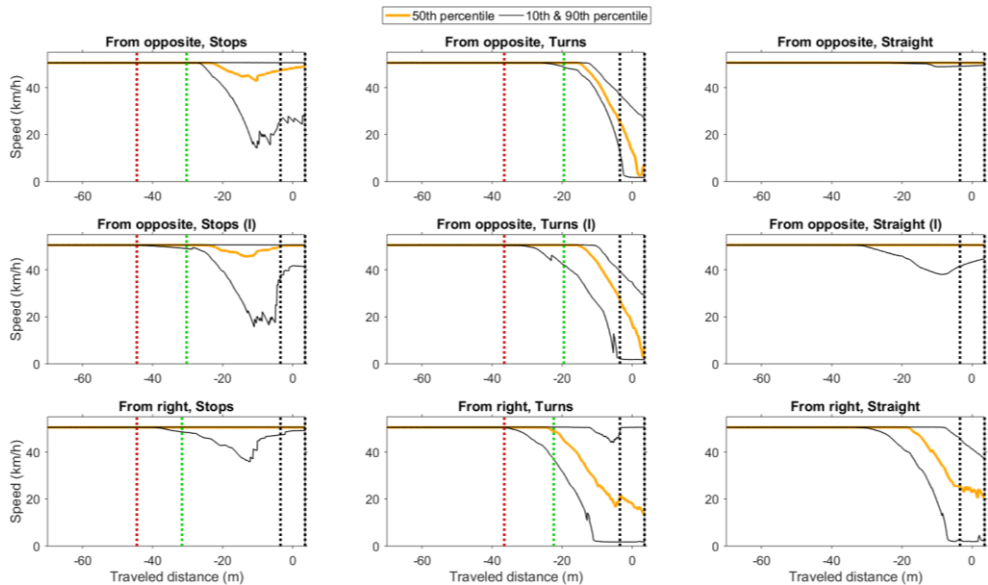


Fig. 4.7. Median, 10th percentile, and 90th percentile of speed across trials per intersection situation. In case a participant came to a stop, data are not shown further. The black vertical lines indicate the start and end of the intersection, the red vertical line indicates the moment when the approaching car started to decelerate, and the green vertical line indicates the moment when the heading of the approaching car started to change.

Table 4.4. Percentage of trials when riders came to a stop (threshold at 5 km/h) before entering the intersection and percentage of trials in which riders were involved in a collision for the four impending-crash situations.

	From opposite, Turns		From opposite, Turns (I)		From right, Turns		From Right, Straight	
	Stop	Crash	Stop	Crash	Stop	Crash	Stop	Crash
No motion	8.82%	76.47%	17.65%	73.53%	50.00%	0.00%	32.35%	8.82%
Motion	0.00%	79.31%	24.14%	65.52%	62.07%	0.00%	31.03%	20.69%

Notes. (I) – The car was indicating a turn.

Crash in the 'From right, Turns' situation could not happen because this car was triggered at the same time as the cars in 'From opposite, Turns' situations as a result of which the potential collision point was located further down the road.

4.3.2.2. Car's direction of travel

When the car approached the intersection from the right and turned ('From right, turns'), riders on average braked 9.34 m earlier compared to the situation where the car approached from the opposite direction and turned ('From opposite, turns'). This effect, which can be seen in Fig. 4.6 (bottom middle vs. top middle), was significant ($t(10) =$

4.79, $p < 0.001$ and $t(9) = 5.61$, $p < 0.001$ for the no-motion and motion configurations, respectively). As can be seen in Table 4.4, riders were less likely to come to a stop before entering an intersection when the car approached from the opposite direction as compared to situations when the car approached from the right intersecting road.

4.3.3. Comparison of braking performance between the motion and no-motion configurations

Fig. 4.6 shows the mean brake position and Table 4.3 shows the means and standard deviations of the brake initiation moment, maximum brake position, and the distance from initiating of braking to the point of maximum braking (i.e., brake rise distance) for the two motion configurations. The results of paired sample t-tests did not show a significant effect of simulator motion on the maximum brake position ($p > 0.215$ for each of the nine situations) nor on brake rise distance ($p > 0.131$ for each of the nine situations). Lastly, no substantial differences were observed in the initiation of the braking maneuver between the motion and no-motion configurations ($p > 0.022$ for each of the nine situations).

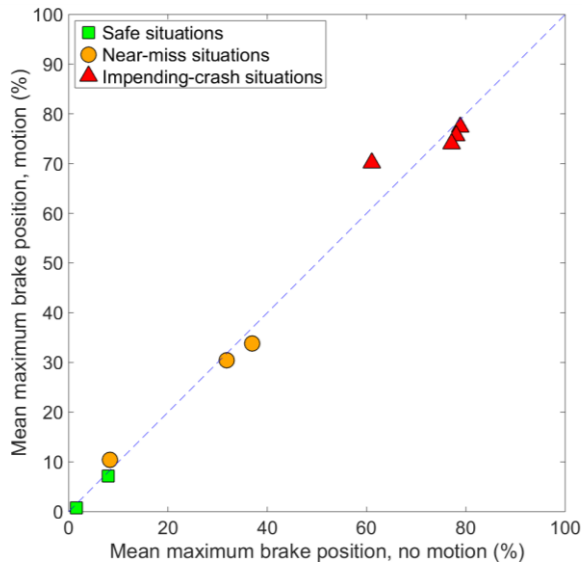


Fig. 4.8. Mean maximum brake position for the nine scenarios shown in Table 4.3, for the no-motion configuration and the motion configuration. The diagonal dashed line is the line of unity.

Further illustration for the lack of effect of motion is provided in Figs. 4.8 and 4.9. Fig. 4.8 shows the maximum brake position for the nine intersection situations. It can be seen that the effect of situation is stronger than the effect of motion; the correlation between the values for the two configurations was close to unity ($r = 0.99$, $n = 9$). Fig. 4.9 shows

a bimodal distribution of the maximum brake position; participants either braked hard or did not brake, with relatively few instances of mild braking (5–40%).

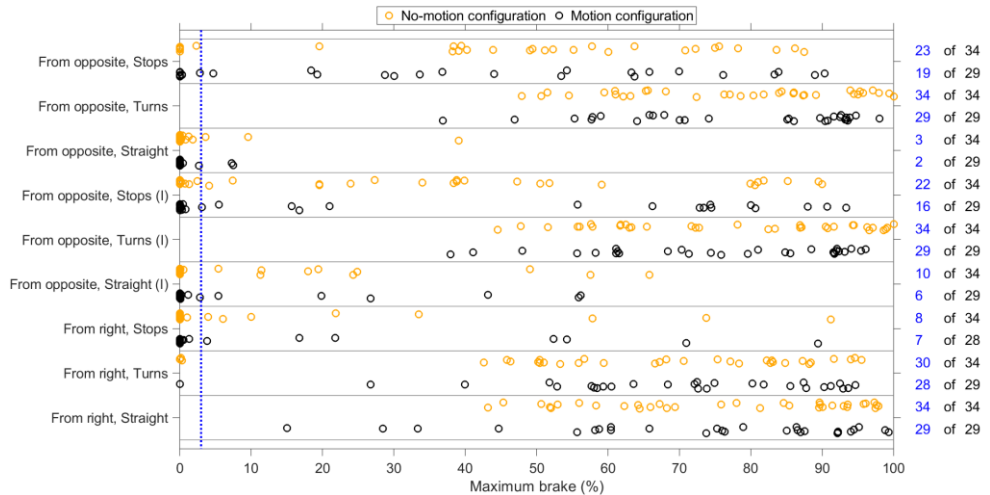


Fig. 4.9. The maximum brake position prior to entering the intersection. Each marker represents a single trial. Blue numbers represent the number of trials in which participants pressed the brakes (threshold at 3% brake input).

4.4. Discussion

Accident statistics show that a frequent crash scenario involving a PTW rider is a crash with a car at an intersection (Clarke et al., 2007; MAIDS, 2009). An in-depth investigation of PTW-car accidents showed that car drivers often failed to perceive the oncoming motorcycle, whereas the PTW riders failed not only in perception but also in executing an avoidance maneuver, such as too weak braking (Penumaka et al., 2014). To study this issue from the perspective of the PTW rider, we performed a simulator study that compared riders' braking performance for impending-crash, near-miss, and safe intersection situations.

The results showed that riders initiated braking right after the car from the opposite direction made a heading change that could signal an imminent threat. The riders initiated braking later (i.e., when they were closer to the intersection) in impending-crash situations compared to near-miss situations. This finding can be explained by the fact that riders appeared to brake immediately after a change in the car's heading, which occurred earlier in near-miss situations than in the impending-crash situations.

Results further indicate that, in situations where a car driver suddenly initiates a left turn, riders are often unable to avoid a collision. It should be noted, however, that the approach speed was fixed at 50 km/h and riders were instructed to try to keep this speed as long as they could and brake only to avoid an upcoming crash. Crundall et al. (2013) showed that expert riders tend to slow down when approaching an intersection, indicating

that not only 'bottom-up' visual cues but also 'top-down' expectancies guide riders' behavior. A similar account is provided by Summala and Rasanen (2000), who illustrated the interaction of top-down factors and bottom-up factors leading up to cyclist-driver crashes. The results from our study suggest that such precautionary strategies are essential for safety, as a purely detective/reactive behavior of the rider is not enough to avoid a collision.

In line with the findings from previous studies on the importance of the car's indicator (Huertas-Leyva et al., 2017; Lee & Sheppard, 2016), riders initiated their braking maneuver slightly earlier when the car was indicating the turn as compared to when the indicator was off. However, the motion of the car and change of heading had stronger effects on the initiation of braking than the indicator signal, as inferred from the fact that riders were unlikely to brake in safe situations even if the turn signal was on. According to the instructions that we provided, participants should not brake when the car continued straight or stopped. In other words, the indicator had to be ignored in these two situations. The effect of the indicator could be smaller in our study as compared to on-road riding because, in reality, the cars' indicator would guide the rider's expectancies and thereby cause the rider to slow down. Furthermore, we note that in real-life cases, riders may be able to anticipate what other road users will do, not only based on the turn indicator but also with the help of other types of precursors or foreshadowing elements (Underwood et al., 2011; Vlakveld, 2014). Examples of such precursors, which were not simulated in our study, include the pre-positioning of the lateral position of the car, additional conflicting vehicles, road markings, head orientation, and eye contact. Future research could employ a more varied visual environment in which multiple road features (e.g., signs, lights, multiple road users) are present, thereby placing high demands on anticipation skills.

Riders initiated their braking maneuver in crash situations earlier when the car was approaching from the right compared to situations when the car approached the intersection from the opposite direction. This effect corresponds to the relatively high percentage of stops before the intersection in the 'car from right' situations. One plausible explanation is that the car from the right is on a collision course with the rider, whereas the car coming from the opposite direction is on a collision course only when it turns to its left. Accordingly, in the car-from opposite situations, the riders started to brake only when visual information such as the car's indicator or heading in combination with high speed could be observed.

The second aim of this research was to compare riders' braking performance when longitudinal motion cues are provided by a motion platform compared to a no-motion simulator configuration. Our results did not show detectable effects of motion on the riders' braking behavior. This result appears to contradict literature that indicates that drivers brake more smoothly when motion cues are enabled as compared to when they are disabled (e.g., De Groot et al., 2011; Siegler et al., 2001) as well as more general studies showing that simulator motion can have strong effects on driving behavior (Berthoz et al., 2013; Shyrokau et al., 2018).

Apart from statistical power, three possible explanations for the discrepancy between our results and the literature can be thought of. First, because the riders approached the intersection using cruise control and steering input did not affect the virtual motorcycle, motion cues were unavailable before the rider started to brake in both the no-motion and motion conditions. This means that the effects of motion on the riders' risk perception and subjective presence in the virtual environment may have been limited; only after the rider started to brake, he/she could feel the motion. Second, we showed that the riders' decisions were rather binary: short-lasting hard braking or no braking (Fig. 4.9). This observation ties into theories about open-loop versus closed-loop manual control (Jagacinski & Flach, 2003). In particular, if riders "slam on the brakes to avoid a collision" (Jagacinski & Flach, 2003, p. 67), no association between braking control and motion feedback ought to be expected. A third explanation for the lack of observable motion effects concerns the motion cueing algorithm itself. It is possible that our adaptive filter-based algorithm as detailed in the Supplementary material yielded a too sluggish response for the highly dynamic braking maneuver under investigation. Thus, the lack of effect by no means implies that motion would not have effects for other types of riding/driving tasks and other types of motion drive laws. It remains to be investigated whether motion affects closed loop braking behavior. This research question could be studied in non-emergency tasks such as approaching an intersection where a rider does not have the right of way or before entering a turn.

Several limitations should be considered when interpreting the present results. First, only 12 people participated, raising questions about statistical power (i.e., 1 minus the false-negative rate), false positives (Button et al., 2013), and generalizability. The small sample size is a concern for the results for the turn indicator, where significant effects may plausibly be expected if larger samples were used. On the other hand, some of the other observed effects presented in this paper are very strong and may not require larger samples. Specifically, the effects concerning the car's direction of travel on the participant's behavior were strong and significant ($p < 0.001$), suggesting high replicability. Also, the finding that motion increases self-reported physical demands and effort is interpretable from a biomechanics viewpoint and thus expected to be replicable. Also, the fact that participants in near-miss scenarios braked harder as compared to safe scenarios, but less hard as compared to impending-crash scenarios, is interpretable and strong, with little overlap of distributions (see also Fig. 4.7). In summary, we argue that the present sample size is a limitation for some of our findings (e.g., effect of the indicator), but still sufficient for our primary research purposes. It should be reminded that our type of research involves ethical and safety challenges regarding motion sickness after-effects (Brooks et al., 2010; Dziuda et al., 2014). Hence, we would advise other researchers not to test more participants than needed if they were to conduct this type of research. The current results show a learning curve where participants grew accustomed to the fact that they did not have to brake in the safe situations, and gradually braked less hard in the near-miss and impending-crash situations (Supplementary material, Fig. S4).

It would be interesting to examine how these trends develop in an even larger number of trials.

A second limitation is that our study aimed to investigate whether riders are capable of avoiding a potential collision based on ‘bottom up’ visual cues in situations where a crash could be expected. In reality, situations in which a car driver does not give right of way are encountered only rarely. Instead, on the road, riders may show a later initiation of braking in case the situation is not expected by the rider (Green, 2000; Olson & Sivak, 1986) as well as anticipatory braking before the relevant visual cues are available. More research should be conducted to understand to what extent a precautionary approaching strategy could significantly reduce the number of crashes.

Third, the realism of the simulator deserves further consideration. Future research could employ a more realistic PTW dynamics model, allowing for the in-depth examination of brake modulation of the front and rear brakes and motorcycle stability in emergency braking conditions (for models see Corno et al., 2008; Limebeer et al., 2001). The virtual environment built in PreScan and projected in the Oculus Rift DK2 resulted in a limited screen resolution. For this reason, the car’s headlight had to be used instead of the car’s indicator light. This limitation is relatively easily countered in future research, as the resolution and refresh rate of the head-mounted display is rapidly increasing (e.g., Vieri et al., 2018). Future research could also use richer virtual environments in order to examine the effect of the aforementioned hazard precursors, although it remains to be seen whether higher visual fidelity would improve the validity of research data (Lee, 2004).

4.5. Conclusions and recommendations

In conclusion, riders’ braking patterns differed between impending-crash, near-miss, and safe situations: the more dangerous the situation, the more likely riders were to brake and the harder they braked. Riders appear to brake in response to a deviation in the approaching car’s heading. Additionally, we showed that riders were often unable to avoid a collision with the car in impending-crash conditions.

Possible remedies to PTW-car crashes could be adjustments in road design (e.g., the presence of a left-turn lane), automated emergency braking for PTWs (Savino et al., 2016), and vehicle-to-vehicle communication technologies for providing warnings in advance (Houtenbos et al., 2017). Furthermore, we see an opportunity for our results to be used in risk awareness training programs (cf. Pollatsek et al., 2006). That is, it would be valuable for PTW riders to be taught, using a PC-based animation, in which cases crashes are unavoidable, and why it is important to slow down before intersections.

Although we did not observe a significant effect on rider’s emergency braking performance between the two simulator configurations, it may be that this study concerned a particular task for which motion is not needed, or it may be due to the specific parameter settings of the motion cueing algorithm (Supplementary material). It remains to be investigated how motion cues provided by a hexapod would affect riding

performance in tasks such as continuous braking or turning, where closed-loop control is to be expected.

Supplementary material

Supplementary materials (motion cueing algorithm, learning curves), characteristics of the virtual world, an illustrative video of the experiment, and other supplementary files are available at <https://data.4tu.nl/repository/uuid:6b1e0ffb-3606-4095-9702-be34dd3c2d59>.

References

- Berthoz, A., Bles, W., Bühlhoff, H. H., Grácio, B. C., Feenstra, P., Filliard, N., Nusseck, H. G. (2013). Motion scaling for high-performance driving simulators. *IEEE Transactions on Human-Machine Systems* 43, 265–276
- Boer, E. R., Kuge, N., & Yamamura, T. (2001). Affording realistic stopping behavior: A cardinal challenge for driving simulators. *Proceedings of the 1st Human-Centered Transportation Simulation Conference*, Iowa City, Iowa.
- Boer, E. R., Yamamura, T., Kuge, N., & Girshik, A. R. (2000). Experiencing the same road twice: A driver centered comparison between simulation and reality. *Proceedings of the Driving Simulation Conference*, Paris, France.
- Bos, J. E., MacKinnon, S. N., & Patterson, A. (2005). Motion sickness symptoms in a ship motion simulator: Effects of inside, outside, and no view. *Aviation, Space, and Environmental Medicine*, 76, 1111–1118.
- Brooks, J. O., Goodenough, R. R., Crisler, M. C., Klein, N. D., Alley, R. L., Koon, B. L., ... & Wills, R. F. (2010). Simulator sickness during driving simulation studies. *Accident Analysis & Prevention*, 42, 788–796.
- Button, K. S., Ioannidis, J. P., Mokrysz, C., Nosek, B. A., Flint, J., Robinson, E. S., & Munafò, M. R. (2013). Power failure: why small sample size undermines the reliability of neuroscience. *Nature Reviews Neuroscience*, 14, 365–375.
- Carsten, O., & Jamson, A. (2011). Driving simulators as research tools in traffic psychology. In B. E. Porter (Ed.), *Handbook of Traffic Psychology* (pp. 87–96). London: Academic Press.
- Celiberti, F., Grottoli, M., Di Gesu, M., Gubitosa, M., & Donders, S. (2016). An overview on the MOTORIST motorcycle simulator. Poster presented at the *Driving Simulation Conference & Exhibition 2016* (DSC 2016 Europe), Paris, France.
- Clarke, D. D., Ward, P., Bartle, C., & Truman, W. (2007). The role of motorcyclist and other driver behaviour in two types of serious accident in the UK. *Accident Analysis & Prevention*, 39, 974–981.
- Corno, M., Savaresi, S. M., Tanelli, M., & Fabbri, L. (2008). On optimal motorcycle braking. *Control Engineering Practice*, 16, 644–657.

- Crundall, E., Stedmon, A. W., Saikayasis, R., & Crundall, D. (2013). A simulator study investigating how motorcyclists approach side-road hazards. *Accident Analysis & Prevention, 51*, 42–50.
- Davoodi, S. R., & Hamid, H. (2013). Motorcyclist braking performance in stopping distance situations. *Journal of Transportation Engineering, 139*, 660–666.
- Davoodi, S. R., Hamid, H., Pazhouhanfar, M., & Muttart, J. W. (2012). Motorcyclist perception response time in stopping sight distance situations. *Safety Science, 50*, 371–377.
- De Groot, S., De Winter, J. C., Mulder, M., & Wieringa, P. A. (2011). Nonvestibular motion cueing in a fixed-base driving simulator: Effects on driver braking and cornering performance. *Presence: Teleoperators and Virtual Environments, 20*, 117–142.
- De Winter, J. C. F., Van Leeuwen, P. M., & Happee, P. (2012). Advantages and disadvantages of driving simulators: A discussion. In *Proceedings of Measuring Behavior* (pp. 47–50), Utrecht, The Netherlands.
- Drury, C. G., & Pietraszewski, P. (1979). The motorists' perception of the bicyclists' hand signals. *Ergonomics, 22*, 1045–1057.
- Dziuda, Ł., Biernacki, M. P., Baran, P. M., & Truszczyński, O. E. (2014). The effects of simulated fog and motion on simulator sickness in a driving simulator and the duration of after-effects. *Applied Ergonomics, 45*, 406–412.
- Ecker, H., Wassermann, J., Hauer, G., Ruspekhofer, R., & Grill, M. (2001a). Braking deceleration of motorcycle riders. *Proceedings of the International Motorcycle Safety Conference*, Orlando Florida, USA.
- Ecker, H., Wassermann, J., Ruspekhofer, R., Hauer, G., & Winkelbauer, M. (2001b). Brake reaction times of motorcycle riders. *Proceedings of the International Motorcycle Safety Conference*, Orlando Florida, USA.
- Green, M. (2000). 'How long does it take to stop?' Methodological analysis of driver perception-brake times. *Transportation Human Factors, 2*, 195–216.
- Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. In P. A. Hancock & N. Meshkati (Eds.), *Human mental workload* (pp. 139–183). Amsterdam: North-Holland B.V.
- Houtenbos, M., De Winter, J. C. F., Hale, A. R., Wieringa, P. A., & Hagenzieker, M. P. (2017). Concurrent audio-visual feedback for supporting drivers at intersections: A study using two linked driving simulators. *Applied Ergonomics, 60*, 30–42.
- Huertas-Leyva, P., Nugent, M., Savino, G., Pierini, M., Baldanzini, N., & Rosalie, S. (2017). Identification of emergency braking performance distinguishing level of skills of motorcycle riders in an integrated real-life perceptual-action task (Paper 322). In *Proceedings of Road Safety and Simulation International Conference*, The Hague, The Netherlands.
- Jagacinski, R. J., & Flach, J. M. (2003). *Control theory for humans: Quantitative approaches to modeling performance*. CRC Press.

- Jamson, H., & Smith, P. (2003). Are you used to it yet? Braking performance and adaptation in a fixed base driving simulator. In *Proceedings of the Driving Simulation Conference North America*, Detroit, Michigan.
- Kennedy, R. S., Lane, N. E., Berbaum, K. S., & Lilienthal, M. G. (1993). Simulator Sickness Questionnaire: An enhanced method for quantifying simulator sickness. *The International Journal of Aviation Psychology*, 3, 203–220.
- Lee, J. D. (2004). Simulator fidelity: How low can you go? *48th Annual Meeting of the Human Factors and Ergonomics Society*, Santa Monica, CA.
- Lee, Y. M., & Sheppard, E. (2016). The effect of motion and signalling on drivers' ability to predict intentions of other road users. *Accident Analysis & Prevention*, 95, 202–208.
- Limebeer, D. J., Sharp, R. S., & Evangelou, S. (2001). The stability of motorcycles under acceleration and braking. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, 215, 1095–1109.
- MAIDS. (2009). *Motorcycle Accident In-depth Study MAIDS: In-depth investigations of accidents involving powered two wheelers* (Final Report 2.0). Brussels: The European Association of Motorcycle Manufacturers ACEM.
- Oculus VR. (2014). *Oculus developer guide: SDK Version 0.4*. Irvine, California: Oculus VR, LLC.
- Olson, P. L., & Sivak, M. (1986). Perception-Response time to unexpected roadway hazards. *Human Factors*, 28, 91–96.
- Pai, C. W. (2011). Motorcycle right-of-way accidents—a literature review. *Accident Analysis & Prevention*, 43, 971–982.
- Penumaka, A. P., Savino, G., Baldanzini, N., & Pierini, M. (2014). In-depth investigations of PTW-car accidents caused by human errors. *Safety Science*, 68, 212–221.
- Pollatsek, A., Narayanaan, V., Pradhan, A., & Fisher, D. L. (2006). Using eye movements to evaluate a PC-based risk awareness and perception training program on a driving simulator. *Human Factors*, 48, 447–464.
- Savino, G., Pierini, M., Thompson, J., Fitzharris, M., & Lenné, M. G. (2016). Exploratory field trial of motorcycle autonomous emergency braking (MAEB): considerations on the acceptability of unexpected automatic decelerations. *Traffic Injury Prevention*, 17, 855–862.
- Shyrokau, B., De Winter, J. C. F., Stroosma, O., Dijksterhuis, C., Loof, J., Van Paassen, M. M., & Happee, R. (2018). The effect of steering-system linearity, simulator motion, and truck driving experience on steering of an articulated tractor-semitrailer combination. *Applied Ergonomics*, 71, 17–28.
- Siegler, I., Reymond, G., Kemeny, A., & Berthoz, A. (2001). Sensorimotor integration in a driving simulator: contributions of motion cueing in elementary driving tasks. In *Proceedings of Driving Simulation Conference* (pp. 21–32), Sophia Antipolis, France.
- Stedmon, A. W., Hasseldine, B., Rice, D., Young, M., Markham, S., Hancox, M., Brickell, E., & Noble, J. (2009). 'MotorcycleSim': An evaluation of rider interaction with an innovative motorcycle simulator. *The Computer Journal*, 54, 1010–1025.

- Summala, H., & Rasanen, M. (2000). Top-down and bottom-up processes in driver behavior at roundabouts and crossroads. *Transportation Human Factors*, 2, 29–37.
- Underwood, G., Crundall, D., & Chapman, P. (2011). Driving simulator validation with hazard perception. *Transportation Research Part F: Traffic Psychology and Behaviour*, 14, 435–446.
- Vavryn, K., & Winkelbauer, M. (2004). Braking performance of experienced and novice motorcycle riders—results of a field study. In *Proceedings of the 4th International Conference on Transport and Traffic Psychology*, Nottingham, England.
- Vieri, C., Lee, G., Balram, N., Jung, S. H., Yang, J. Y., Yoon, S. Y., & Kang, I. B. (2018). An 18 megapixel 4.3 "1443 ppi 120 Hz OLED display for wide field of view high acuity head mounted displays. *Journal of the Society for Information Display*, 26, 314–324.
- Vlakveld, W. P. (2014). A comparative study of two desktop hazard perception tasks suitable for mass testing in which scores are not based on response latencies. *Transportation Research Part F: Traffic Psychology and Behaviour*, 22, 218–231.
- Walker, I. (2005). Signals are informative but slow down responses when drivers meet bicyclists at road junctions. *Accident Analysis & Prevention*, 37, 1074–1085.
- Walker, I., & Brosnan, M. (2007). Drivers' gaze fixations during judgements about a bicyclist's intentions. *Transportation Research Part F: Traffic Psychology and Behaviour*, 10, 90–98.
- Westerhuis, F., & De Waard, D. (2017). Reading cyclist intentions: Can a lead cyclist's behaviour be predicted? *Accident Analysis & Prevention*, 105, 146–155.
- Wilde, G. J. (1976). Social interaction patterns in driver behavior: An introductory review. *Human Factors*, 18, 477–492.

CHAPTER 5

RIDING PERFORMANCE ON A CONVENTIONAL BICYCLE AND A PEDELEC IN LOW SPEED EXERCISES: OBJECTIVE AND SUBJECTIVE EVALUATION OF MIDDLE-AGED AND OLDER PERSONS

This study investigated cycling performance of middle-aged (30–45 years old; $n = 30$) versus older (65+ years; $n = 31$) participants during low-speed tasks for which stabilization skills are known to be important. Additionally, participants' self-ratings of their cycling skills and performance were assessed. Participants rode once on a conventional bicycle and once on a pedelec, in counterbalanced order. Three standardized tasks were performed: (1) low-speed cycling, (2) acceleration from a standstill, and (3) shoulder check. During Tasks 1 and 3, the mean absolute steering angle (a measure of the cyclist's steering activity) and the mean absolute roll rate (a measure of the amount of angular movement of the frame) were significantly greater for older participants than for middle-aged participants. These large lateral motions among older cyclists may indicate a difficulty in controlling the inherently unstable system. Comparing the conventional bicycle and the pedelec, participants reached a 16 km/h threshold speed in Task 2 sooner on the pedelec, an effect that was most pronounced among the older participants. Correlations between skills assessed with the Cycling Skill Inventory and actual measures of cycling performance were mostly not statistically significant. This indicates that self-reported motor-tactical and safety skills are not strongly predictive of measures of actual cycling performance. Our findings add to the existing knowledge on self-assessment of cycling skills, and suggest that age-related changes in psychomotor and sensory functions pose hazards for cycling safety.

Kováčsová, N., De Winter, J. C. F., Schwab, A. L., Christoph, M., Twisk, D. A. M., & Hagenzieker, M. P. (2016). Riding performance on a conventional bicycle and a pedelec in low speed exercises: Objective and subjective evaluation of middle-aged and older persons. *Transportation Research Part F: Traffic Psychology and Behaviour*, 42, 28–43.

5.1. Introduction

Across the period 2000–2009, a steady decline in cycling fatality rates has occurred in Europe, but the number of seriously injured cyclists has actually increased in the Netherlands (see OECD/ITF, 2013 for international trends in cycling safety). When expressed per kilometer traveled by bicycle, older cyclists (aged 65 or over) are the most vulnerable group (SWOV, 2013). Factors that may explain the increase of seriously injured cyclists are (1) population aging associated with a decrease of physical and cognitive functions (increasing the likelihood of a crash) and an increase of fragility (increasing the likelihood of injury in case of a crash) (OECD, 2001), (2) changes in the types of bicycles used (e.g., conventional bicycles vs. pedelecs), and (3) growing exposure because an increasing number of trips are completed and longer distances are traveled on (electric) bicycles (Fyhri & Fearnley, 2015). This chapter presents the results of a field experiment investigating self-reported and actual performance among middle-aged and older cyclists. Cycling performance on both a pedelec and a conventional bicycle was investigated during low-speed tasks for which stabilization skills are known to be important.

5.1.1. Potential risks of pedelecs for older persons

Pedelecs (also called electric bicycles or e-bikes) have gained enormous popularity in the last decade. About 5% of people in the Netherlands own a pedelec, with a relatively high rate of ownership and usage among women and people aged 60 and over (Van Boggelen et al., 2013). A high usage of pedelecs among older people has also been observed in Austrian and German studies (GDV, 2014; Wolf & Seebauer, 2014).

Although pedelecs provide benefits to older persons, there are some safety concerns for this age group. It is well known that older people have less accurate sensory abilities (i.e., visual, vestibular, and somatosensory) and slower average reaction times than young persons (e.g., Jensen, 2006; Shaffer and Harrison, 2007). Therefore, older persons may have difficulties in situations that require agile reactions and active (low-speed) stabilization of the bicycle. Furthermore, age is associated with a decline in physical strength (Kallman et al., 1990).

A case control study by Schepers et al. (2014) showed that people using pedelecs, after controlling for age, gender, and exposure, were more likely to be involved in a crash that required treatment at an emergency department than people using conventional bicycles. Moreover, analyses of crash characteristics have shown that pedelecs are involved in a disproportionately high number of single bicycle crashes, suggesting that cycling at high speed, mounting and dismounting, or difficulty in maneuvering may be causal factors (Papoutsis et al., 2014; Schepers et al., 2014; Weber et al., 2014).

5.1.2. The distinction between riding skill and riding style

Both riding skill ('performance') and riding style ('behavior') are crucial for assessing a person's cycling safety (for a review on skill versus style, see Elander et al., 1993).

Riding style refers to an individual's habits and preferences in riding the bicycle, such as crossing behavior at intersections and speed choice. Comparisons between the cycling speeds of conventional bicycles and pedelecs have shown that participants on pedelecs adopt an average cruising speed that is 1.5–4 km/h higher than on conventional bicycles (Dozza et al., 2016; Schleinitz et al., 2017; Vlakveld et al., 2015).

Rider skill refers to how good a person is at controlling the vehicle (e.g., accelerating, steering) and at maneuvering in accordance with the prevailing circumstances on the road (e.g., avoiding an obstacle) (Michon, 1985). Cyclists balance the bicycle-rider system by means of two primary control mechanisms: steering and leaning (Kooijman & Schwab, 2013). The corresponding control inputs are the steering torque (applied by the cyclist through the handlebar) and the upper body lean torque (applied by the cyclist by leaning relative to the bicycle; Schwab et al., 2008). Observations of a cyclist riding through a town showed that little upper body lean occurred when performing normal maneuvers and that the cyclist mainly used steering as control input (Kooijman et al., 2009).

Rider performance is typically evaluated by means of measures related to the steering and roll angle of the bicycle. The steering angle represents the rotation of the front assembly with respect to the bicycle frame, and the roll angle represents the left/right rotational movement of the bicycle frame about its longitudinal axis. Cain (2013) showed that the correlation between steer and roll angular velocities increased among children during the learning process, indicating that children learned to steer in the direction of roll. Fonda et al. (2017) found that experienced cyclists had steer and roll motions of smaller amplitude and of a lower rate than inexperienced cyclists. The previous studies that investigated how people control a bicycle have been conducted on children and middle-aged cyclists. It is yet unknown how an age-related decline in motor, sensory, and cognitive functioning is associated with rider performance.

Thus far, research on individual differences in rider performance for different types of bicycles has been sparse. Some experimental studies have been conducted with the purpose of evaluating the effects of bicycle design on handling performance (e.g., Godthelp & Wouters, 1980; Mortimer et al., 1976; Rice & Roland, 1970). These studies showed that humans are capable of successfully riding bicycles with different handlebar configurations and different basic designs of bicycles, which suggests that cyclists may be able to successfully transfer their riding skills from a conventional bicycle to a pedelec. Although conventional bicycles and pedelecs have similar dimensions, due to their battery and motor, pedelecs are typically heavier than conventional bicycles (MacArthur & Kobel, 2015).

5.1.3. Self-assessment of skill

The self-assessment of skills has an important role in so-called 'calibration', a process whereby a rider adjusts the task demands to his/her perceived skills, and which is assumed to be essential in road safety (Kuiken & Twisk, 2001). Moreover, it has been argued that the understanding of one's own capabilities plays an important role in the

learning process and in the prevention of poor decision making and risky behaviors (Horrey et al., 2015; Keskinen & Hernetkoski, 2011; Kuiken & Twisk, 2001).

With the aim of investigating whether car drivers have an accurate perception of their own skills, several different methods have been used (Sundström, 2008). Sometimes (a) drivers had to compare their skills with the skills of the 'average driver' or their peers, (b) drivers had to rate their own skills on specific aspects of driving skill such as is in the Driving Skill Inventory (Lajunen & Summala, 1995), or (c) the self-reported skill was compared with actual driving performance. Research on the self-assessment of cycling skills is scarce. In early studies by Daniels et al. (1976) and Drury and Daniels (1980), cyclists ($n = 25$) rated their riding skills (from extremely skilled to no skill) and cautiousness (from extremely cautious to not cautious) and performed four cycling exercises (slalom, circle speed, braking, and straight-line tracking). Of the reported correlations between self-assessed skill/cautiousness and ten objective measures of riding speed and accuracy, only two correlations were statistically significant: self-rating of skill correlated positively with the average speed in a circle exercise, and self-rating of caution correlated negatively with stopping distance. These findings suggest that self-assessment of cycling skill might not be strongly predictive of actual cycling measures.

5.1.4. The present study

The study in this paper is part of a larger field operational test with an instrumented conventional bicycle and a pedelec conducted at the SWOV Institute for Road Safety Research in the Netherlands from July until September 2013. The aim of this field test was to assess the effect of pedelecs on cycling performance and behavior among middle-aged versus older persons, with an emphasis on cycling safety. The field test consisted of a 30-min ride on a pedelec and a 30-min ride on a conventional bicycle. After each of these two rides, the participants conducted standardized exercises on an empty parking lot. In addition to collecting objective data measured by devices mounted on the bicycles, questionnaires were administered prior and after the field testing, and cyclists' workload, balance, and grip strength were measured.

Previous publications on this field test have focused on rider behavior (speed choice) and workload during the 30-min rides (Vlakveld et al., 2015), on the specific procedures during mounting maneuvers in relation to rider speed and balance (Platteel et al., 2015), and on self-reported skills of older versus middle-aged cyclists (De Groot-Mesken & Commandeur, 2014). The present study focuses on cyclists' performance during three exercises on an empty parking lot: (1) low-speed cycling, (2) acceleration from a standstill, and (3) shoulder check. Our first aim was to investigate cyclists' performance regarding the control of a conventional bicycle and a pedelec, and to establish how this performance is associated with participants' age, reaction time, and grip strength. The second aim was to investigate how rapidly cyclists accelerate, and which speeds they adopt during these exercises. The third aim was to assess cyclists' self-ratings of their general cycling skills and performance during the field test, and to examine the correlation

between general cycling skills and actual cycling performance. Specifically, this study addressed the following four research questions.

1. *How is age associated with cycling performance and speed?*
2. *Do participants on a pedelec adopt different speeds than the same participants on a conventional bicycle?*
3. *How strongly are self-reported general cycling skills correlated with actual cycling performance?*
4. *Do participants believe that they performed particular skills better on the conventional bicycle than on a pedelec, or vice versa?*

5.2. Method

5.2.1. Participants

Sixty-one participants were recruited through invitation letters, flyers, and the SWOV research participant database. Addresses for the dissemination of the invitation letters were obtained from a marketing/communication company based on two age groups (30–39 vs. 65–79 years) and living area (The Hague and its surroundings). Five hundred letters were sent to the middle-aged group and another 500 letters were sent to the older-age group. Only persons who cycled regularly and who were in good health were eligible to participate. Pedelec riding experience was not required (1 middle-aged and 9 older participants reported that they own a pedelec). Moreover, only persons who were either 30–45 years old or 65 years old or older were included in the study.

Table 5.1. Demographic characteristics of the participants for Tasks 1, 2, and 3.

Age group	Characteristics	Total Sample	Task 1 <i>Low-speed cycling</i>	Task 2 <i>Accelerating</i>	Task 3 <i>Shoulder check</i>
Middle-aged participants	<i>N</i>	30	30	30	29
	Females	17	17	17	17
	Mean age (<i>SD</i>)	37.7 (4.2)	37.7 (4.2)	37.7 (4.2)	37.7 (4.3)
Older participants	<i>N</i>	31	29	28	23
	Females	14	13	12	9
	Mean age (<i>SD</i>)	70.0 (4.2)	69.9 (4.2)	69.6 (3.9)	69.6 (3.8)

Demographic characteristics of both age groups are shown in Table 5.1. One participant withdrew from the study due to safety reasons and one participant was excluded from the analyses because of a failure of the speed-measuring device. In addition, one participant was excluded from the analyses of Task 2 because of not performing the task correctly. Seven participants were excluded from the analyses for Task 3 due to technical problems with the rider-facing camera (1 participant), not performing the task correctly (2 participants), and participants' withdrawal from the task

(4 participants). The withdrawn participants considered the task as difficult and decided to not complete the task after (a) hearing the instruction (1 participant) or (b) an incorrect first try (3 participants).

5.2.2. Data collection and procedure

Prior to the test day, participants received a self-report questionnaire with items on demographic characteristics, travel behavior, and skills (Cycling Skill Inventory; De Groot-Mesken & Commandeur, 2014). At the beginning of the testing session, the details of the study were explained to the participants, after which an informed consent form was signed¹. Prior to riding the instrumented bicycle, participants' grip strength and baseline reaction times on the peripheral detection task (PDT) were measured (see Vlakveld et al., 2015 for a description of PDT). Next, participants were equipped with the bicycle helmet, PDT equipment, and a backpack.

The field experiment was conducted in daylight and dry weather conditions. Each participant rode the approximately 3.5 km long route four times: one practice ride and one test ride on both the conventional bicycle and pedelec. After the test ride on each bicycle, participants were asked to perform four standardized tasks on the parking lot area: (1) cycling at low speed, (2) accelerating up to 17 km/h and then brake, (3) indicating direction with the left hand and looking backward, (4) mounting and dismounting. Thus, a participant rode a practice ride, a test ride, and performed tasks on the empty parking lot on the one type of the bicycle (i.e., conventional bicycle or pedelec). After this, the participant returned to the starting point to change the bicycle and repeated the procedure with the other type of bicycle. The order of bicycle type was counterbalanced across participants. The first three tasks on the parking lot were analyzed in the present study. The PDT device was switched off during the parking lot exercises. For a detailed description of the 3.5 km long route, see Vlakveld et al. (2015).

At the end of the experiment, a final questionnaire on the participants' performance when riding both bicycle types (Cyclist Self-Assessment Scale) was administered. Each session lasted approximately 2.5 h and at the end, participants were reimbursed for their time with a gift card. All instructions and questionnaires were provided to the participants in the Dutch language.

¹ Ethical Considerations

The experiment was performed in compliance with all relevant Dutch legislation. At the time of the experiment, the performing institute SWOV Institute of Road Safety Research did not have an approving institutional review board. However, the study was planned so as to strictly follow the guidelines for ethical conduct of behavioral projects involving human participants proposed by the American Psychological Association. Participants' data protection complies with the rules of the Dutch Dataprotection Authority (Dutch DPA).

5.2.3. Apparatus

Cycling data were collected by two instrumented bicycles (see Fig. 5.1), which were the same model having a step-through frame. The pedelec was a Batavus Socorro Easy model 2012. This bicycle had a rear wheel hub motor that could deliver a maximum power of 250W and a maximum torque of 40 Nm. The electrical assistance was controlled by a pedal force sensor. The pedelec weight was 27.4 kg and was 11.4 kg heavier than the conventional bicycle. The electric engine provided pedaling assistance only when the cyclists pedaled and only up to a speed of 25 km/h. Power support could be set to four levels: no support, low support, normal support, and high support. In the present study, 'normal support' was set and participants were requested to not change this during the whole experiment. Each bicycle had 21 gears. Participants were allowed to change gears when riding the conventional bicycle. However, participants were asked to not change gears when riding the pedelec. The gear ratio influences the force that participants put on the pedals, which in turn determines the power supplied by the support system. By keeping the gear ratio constant, all participants received the same amount of pedaling support at a given speed.

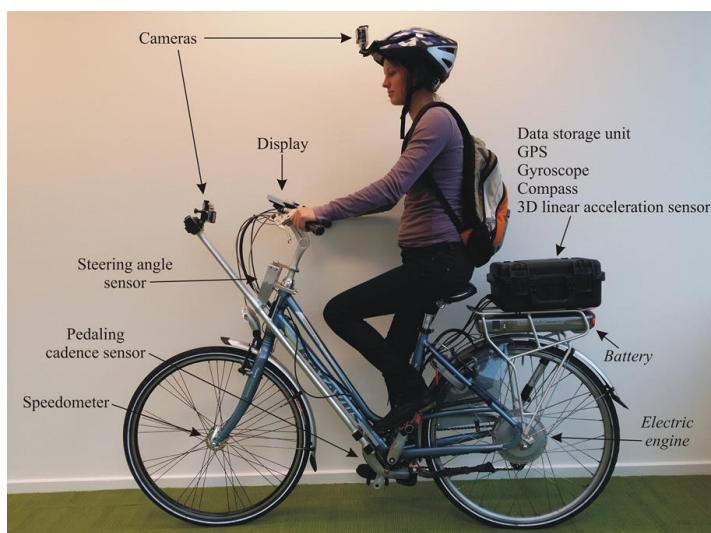


Fig. 5.1. The instrumentation of the pedelec. The instrumented conventional bicycle was not fitted with the battery and electric engine (indicated in italics).

For measuring steering angle, a potentiometer with an angular range up to 360 degrees was mounted at the steering shaft. To measure the roll rate of the bicycle, a single axis sensor (Silicon Sensing CRS03) mounted on the back of the bicycle was used. Speed was measured with a generator embedded in the hub of the front wheel. Steering angle, roll rate, and speed data were logged at a sampling rate of 50 Hz. To inform cyclists about their speed, a display was mounted on the handlebar.

5.2.4. Description of the tasks

The tasks conducted on the parking lot area were offered to all participants in the same order. The instruction for each task was provided after completing the previous task. In case a participant did not complete a task correctly for the first time, two more tries were offered (one more try for Task 3). In all tasks, participants were instructed to ride straight ahead but no straight-line markers on the ground were available.

The instruction and exclusion criteria for each task were as follows:

1) *Task 1: Low-speed cycling*

The instruction for the participants was the following: *“When I whistle, start cycling slowly at 7 km/h until you reach the last pylon. Next, you can turn around and cycle back at your own pace.”*

2) *Task 2: Accelerating*

The participants received the following instruction: *“Try to reach a speed of 17 km/h as quickly as possible and subsequently come to standstill by braking as hard as possible. You do not have to get off the bike.”* Due to large individual differences in braking (from rapid/immediate braking to slow/continuous braking), only the acceleration part was analyzed in the present study. One participant was excluded because she did not reach the instructed speed.

3) *Task 3: Shoulder check*

The participants were instructed as follows: *“When I whistle, start cycling at your own pace. When passing the first traffic pylon, please indicate direction with your left hand, and when I whistle again look over your left shoulder. Try to see how many hands I raise (zero, one, or two).”* Fig. 5.2 shows an overview of the subtasks of Task 3. It should be noted that there were individual differences in the way participants carried out the particular subtasks. Left-hand-turn and looking-over-the-left-shoulder events were coded based on the videos recorded by the rider-facing camera. Two participants were excluded because they did not continue straight after performing the subtasks, that is, started to turn the bicycle to the left while looking backward and/or indicating direction by hand. Participants who did not report correctly how many hands the experimenter raised but otherwise performed the exercise correctly were not excluded (6 participants).

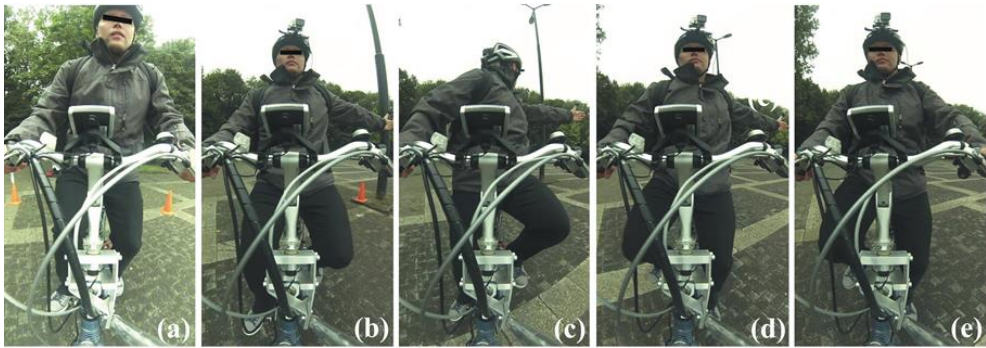


Fig. 5.2. Task 3: Shoulder check; (a) straight cycling, (b) indicating direction with the left hand while looking to the front, (c) looking over the shoulder, (d) looking again to the front while still indicating direction, (e) straight cycling with both hands on the handlebar.

5.2.5. Measures

5.2.5.1. Cycling performance

The following cycling performance measures were calculated for each task, for each participant, and for both bicycles:

Mean absolute steering angle (deg). This measure is the absolute steering angle averaged across time. A large mean absolute steering angle might indicate difficulty in balancing and controlling the bicycle when cycling straight.

Mean absolute roll rate (deg/s). The mean absolute roll rate was used as a measure of the lateral movement speed of the bicycle frame. The bicycle roll rate is closely linked with steer rate as well as with pedaling activity (Moore et al., 2011). A large mean absolute roll rate might indicate difficulties with stabilizing the bicycle.

R² between roll rate and steering rate (between 0 and 1). The peak value of the cross-correlation between roll rate and steering rate was squared to yield a R², being a measure of the similarity between the two signals. The same way of calculating the cross-correlation between bicycle roll rate and steer rate was also used in a previous study on cyclists' performance (Cain, 2013). This measure was calculated only for Task 1 since it was the only task in which the participants rode the bicycles at constant speed across the whole exercise.

Time delay between roll rate and steering rate (s). The corresponding time delay is a measure of how much the steering signal lags behind the roll signal. This measure was calculated also only for Task 1.

Mean speed (km/h). The mean speed was used as a measure of cycling speed.

Total time (s). The total time was used as a measure of time to complete the (sub)task.

For Task 1 (low-speed cycling), since the speed and total distance slightly varied across the participants, some participants completed the task in a shorter time than others. In order to have the same amount of data for each participant, data from 5 up to

20 s (approximate time when all participants had reached the instructed speed of 7 km/h) were analyzed. For Task 2 (accelerating), the above measures were analyzed from the moment the participant rode faster than 0 km/h until reaching 16 km/h. The threshold speed used in the analysis was set at 16 km/h instead of the instructed speed of 17 km/h in order to apply a small buffer that can account for a potential difference/lag between the actual speed and the speed displayed by the device on the handlebar. For Task 3 (shoulder check), the analysis was divided into two parts: (1) '3 s before head start – head start' and (2) 'head start – head end'. This way, we made a distinction between a 3 s relatively stationary period *prior* to head/body movement, and the period *during* head/body movement.

5.2.5.2. Self-reported cycling skills and performance

The Cycling Skill Inventory (CSI; De Groot-Mesken & Commandeur, 2014) is a 17-item scale for assessing an individual's self-reported cycling skills. The CSI was developed based on the taxonomy of motor skills and safety skills that is typically found among car drivers (Lajunen & Summala, 1995). The CSI items were produced by selecting items from Lajunen and Summala's Driver Skill Inventory (DSI) that are relevant also to cyclists (e.g., "knowing how to act in particular traffic situations") and by creating several new skill items that are cycling-specific (e.g., "cycling when it is slippery"). Participants were asked to compare themselves with an average cyclist of the same age. The response options for each item were: 1 (*much better*), 2 (*better*), 3 (*the same*), 4 (*worse*), and 5 (*much worse*).

In another questionnaire – Cyclist Self-Assessment Scale (CSAS), participants rated their performance during their test rides (i.e., 3.5 km rides and exercises on a parking lot) after the entire field testing for the conventional bicycle versus the pedelec. This scale was developed to assess self-ratings of the particular tasks that were performed in the field test. Participants were required to tick a bullet on a seven-point scale (without numbering), in which one pole was the conventional bicycle and the other pole the pedelec. The closer participants indicated their response to one type of bicycle, the more they believed they were able to perform the particular skill better during their test rides on this bike. Response place in the middle of the scale indicated that participants were able to perform the skill equally well on both bicycles. Only items that were related to the first three tasks were analyzed; they were as follows: accelerating from standstill, bicycle control, turning, braking/stopping, keeping balance, and obtaining/maintaining speed.

5.2.5.3. Grip strength and reaction time

The participants' grip strength was recorded using a dynamometer. The handle grip of the dynamometer was adjusted to ensure that it is comfortable in the hand of the participant. The participants were asked to squeeze as hard as possible for about 2 s. The task was performed twice for each hand with a resting period of 15–20 s.

The participants' baseline reaction time was measured using the PDT device while participants were standing next to the bicycle prior to the first practice ride. Participants were asked to respond to the LED light as quickly as possible by pushing a button. The LED light was switched on for 1 s at a time. The inter-stimulus interval was 3–5 s (determined at random) and the task lasted three minutes in total. Thus, a participant performed about 36 reaction time trials in total.

5.2.6. Statistical analyses

First, cycling experience, grip strength, and reaction time among the two age groups were described using the mean and standard deviation. Differences for age were analyzed with independent two-sample *t* tests. The grip strength was averaged across four trials, and the baseline reaction time was averaged across approximately 36 trials.

Next, the factor structure of the Cycling Skill Inventory was assessed. Items of the CSI were subjected to principal axis factor analysis (PAF) followed by direct oblimin rotation. PAF is one of the most common types of exploratory factor analysis (Conway & Huffcutt, 2003; De Winter & Dodou, 2012). Exploratory factor analysis is a statistical method that attempts to explain the off-diagonal elements of the correlation matrix in terms of a small number of common factors; it closely resembles principal component analysis, which is essentially a data reduction method. A minimum factor loading of .30 was used for considering an item to be part of a factor. The mean scores of the CSI factors and the CSAS items were compared between middle-aged and older participants using an independent two-sample *t* test. In addition, frequencies of self-ratings of participant's cycling performance (CSAS) were calculated.

A data quality check revealed that there were some differences in the characteristics (e.g., noise characteristics) of the steering angle and roll rate measurements between the two bicycles. Because even the slightest difference in calibration, sensor fabrication, or sensor attachment would invalidate conclusions, we refrain from interpreting steer and roll differences *between* the conventional bicycle versus pedelec on the steering and roll rate measures. However, any age effect should still be valid, because all participants rode both bicycles, and because middle-aged and older participants were sampled more or less alternately (i.e., there was no correlation between participant number and age [$r = 0.01$, $n = 61$]).

Prior to the statistical analysis of the data collected on instrumented bicycles, the steering, roll rate, and speed signals were filtered with a forward and reverse low-pass filter with a cut-off frequency of 7.5 Hz, 7.5 Hz, and 2.5 Hz, respectively.

Differences between middle-aged and older cyclists in steer and roll rate measures (averaged across both types of bicycles) were analyzed with independent two-sample *t* tests. The mean speed averaged across the time of the (sub)task and time to complete the (sub)task of older participants on a conventional bicycle and a pedelec were compared to those of middle-aged participants. A 2 x 2 mixed design analysis of variance (ANOVA) was performed, with (1) bicycle type (conventional bicycle vs. pedelec) as

within-subjects factor, (2) age (middle-aged vs. older participants) as between-subjects factor, and (3) bicycle type x age group as interaction factor.

In order to explore the relationships between demographic variables, cycling frequency, weekly distance traveled, grip strength, reaction time, self-reported cycling skills (measured by the CSI), and actual cycling performance, Spearman's rank order correlation coefficients were computed. In calculating these correlation coefficients, the cycling performance measures were averaged across both types of bicycles.

5.3. Results

5.3.1. Descriptive results

Descriptive statistics for cycling experience, grip strength, and reaction time are presented in Table 5.2. Middle-aged participants rode their bicycle more often than older participants did. Middle-aged cyclists squeezed the dynamometer significantly harder than older cyclists. The mean z-scores of the grip strength with respect to published age- and gender-based norms of grip strength (Dodds et al., 2014) were -0.48 ($SD = 0.85$, $n = 30$) for the middle-aged participants and -0.56 ($SD = 0.77$, $n = 31$) for the older participants. Differences in reaction time between two age groups were not statistically significant.

Table 5.2. Means, standard deviation, and *t* tests for cycling background variables, grip strength, and reaction time according to age group.

	Middle-aged			Older			Middle-aged vs. older	
	<i>N</i>	Mean	<i>SD</i>	<i>N</i>	Mean	<i>SD</i>	<i>t</i> (<i>df</i>)	<i>p</i>
Kilometers per week	30	43.4	40.2	29	30.1	32.5	1.400 (57)	0.167
Cycling frequency ^a	29	4.21	1.01	30	3.47	1.22	2.525 (57)	0.014
Grip strength (<i>N</i>)	30	348.5	104.1	31	270.6	67.8	3.478 (59)	<0.001
Reaction time (ms)	29	292.7	72.9	31	315.2	75.0	-1.181 (58)	0.242

Notes. *p* values < .05 are in boldface. ^aCycling frequency was indicated on 5-point scale: 1: less than 1 per month, 2: few times per month, 3: 1–2 days per week, 4: 3–4 days per week, 5: 5–7 days per week.

5.3.2. Self-rating of cycling skills

The scree plot (i.e., the eigenvalues of the correlation matrix) of the 17 CSI items indicated that a two-factor solution was most appropriate (the first four eigenvalues were 7.33, 2.83, 1.23, and 1.07). The two-factor solution accounted for 54.9% of the variance: 40.8% and 14.1% for Factor 1 and Factor 2, respectively. The factor loadings are shown in Table 5.3. The first factor consisted of twelve items, which reflect vehicle handling skills and perceptual and social skills related to prevailing circumstances on the road and thus the factor was labeled as 'motor-tactical skills' based on terminology proposed by Michon (1985). The second factor consisted of five items that are similar to the original safety skills factor found among car drivers (Lajunen & Summala, 1995). Thus, this factor was labeled 'safety skills'.

There were no statistically significant differences between middle-aged and older participants for both extracted factors ($p > 0.05$). As can be seen in Table 5.3, participants rated their skills as slightly better than an average cyclist of the same age (i.e., mean score < 3 on the five-point scale).

Table 5.3. Factor loadings, means, and standard deviations of the Cycling Skill Inventory items ($n = 60$).

Item	Middle-aged participants Mean (SD)	Older participants Mean (SD)	Motor-tactical skills	Safety skills
10. Fast reactions	2.43 (0.77)	2.27 (0.64)	0.879	0.019
9. Recognizing hazards in traffic	2.37 (0.76)	2.17 (0.65)	0.839	-0.030
15. Maneuvering smoothly through busy traffic	2.53 (0.78)	2.47 (0.73)	0.821	-0.163
5. Controlling the bicycle	2.53 (0.63)	2.40 (0.67)	0.816	0.149
7. Sudden braking and/or swerving when needed	2.47 (0.73)	2.17 (0.70)	0.806	0.190
2. Knowing how to act in particular traffic situations	2.47 (0.68)	2.57 (0.57)	0.758	-0.184
14. Predicting traffic situations ahead	2.43 (0.63)	2.33 (0.66)	0.749	0.053
17. Showing consideration for other road users	2.47 (0.68)	2.30 (0.60)	0.679	0.143
8. Staying calm in irritating situations	2.37 (0.67)	2.30 (0.79)	0.547	0.165
1. Cycling when it is slippery	2.90 (0.80)	2.93 (0.78)	0.528	-0.383
4. Tolerating other road users' errors calmly	2.63 (0.81)	2.63 (0.72)	0.502	0.079
11. Yielding to somebody else who does not have right of way	2.53 (0.73)	2.33 (0.71)	0.462	0.260
16. Obeying traffic rules	2.77 (0.68)	2.53 (0.68)	0.010	0.901
13. Cycling carefully	2.90 (0.71)	2.50 (0.68)	0.127	0.682
12. Avoiding unnecessary risks	2.67 (0.66)	2.43 (0.63)	0.200	0.660
6. Adjusting speed to the conditions	2.70 (0.88)	2.37 (0.67)	0.328	0.627
3. Obeying traffic signals	2.80 (0.76)	2.67 (0.61)	-0.112	0.572
% of variance explained			40.8	14.1
Cronbach's alpha^a			0.92	0.84
Number of items			12	5
Mean (SD)^a: Middle-aged participants			2.51 (0.56)	2.77 (0.61)
Mean (SD)^a: Older participants			2.41 (0.47)	2.50 (0.47)

Note. Bold values refer to items with factor loadings of 0.3 or greater that were used in producing the composite scale (values of 0.3 or higher that are not in boldface indicate that the item was not used in producing the composite scale). Participants rated each item from 1 (*much better*) to 5 (*much worse*).

^a Cronbach's alpha, mean, and standard deviation were calculated for the concerning scale.

The majority of middle-aged and older participants rated their 'accelerating from standstill' and 'obtaining/maintaining speed' performance as better when riding the pedelec compared to riding the conventional bicycle (see Table 5.4). In general, participants reported being slightly better on the other four performed tasks when riding the conventional bicycle compared to the pedelec (except for 'braking/stopping' among older cyclists). No significant differences were observed between middle-aged and older cyclists for self-rated cycling performance across two bicycles ($p > 0.05$).

Table 5.4. Frequency distribution and means for performance on both bicycle types rated after the field experiment for middle-aged and older cyclists.

	Middle-aged participants									Older participants								
	N	Frequency ^a							Mean	N	Frequency ^a							Mean
		1	2	3	4	5	6	7			1	2	3	4	5	6	7	
Accelerating from standstill	29	0	1	2	5	2	11	8	5.52	31	3	1	2	5	6	11	3	4.77
Bicycle control	29	1	7	6	13	2	0	0	3.28	31	3	3	4	12	4	3	2	3.90
Turning	30	1	1	11	14	2	1	0	3.60	31	2	2	8	12	2	4	1	3.84
Braking/Stopping	30	2	2	2	22	2	0	0	3.67	31	1	2	0	22	2	4	0	4.10
Keeping balance	30	1	1	5	22	1	0	0	3.70	31	2	2	7	13	3	4	0	3.81
Obtaining/maintaining speed	30	0	1	0	5	5	10	9	5.67	31	0	2	0	4	8	13	4	5.35

^aEach item was rated on a 7-point scale (without numbering), in which one pole was a conventional bicycle (1) and on the other pole was a pedelec (7). An answer placed in the middle of the scale (point 4) indicated that the skill was reported as executed equally well on both bicycles.

5.3.3. Actual cycling performance

The means and standard deviations of the cycling performance measures per age group and per bicycle are shown in Table 5.5. The results of independent two-sample *t* tests for the measures of steering and bicycle roll are also shown in Table 5.5, and a summary of the 2 x 2 mixed design ANOVA results for the speed and time measures is provided in Table 5.6.

5.3.3.1. Steering and roll

Participants in Task 1 performed relatively small mean steering actions (i.e., mean absolute steering angles around 3 deg, see Fig. 5.3 top) while cycling at average speeds of about 7–8 km/h, which is a speed range for which human stabilizing is needed. Older participants had a significantly higher mean absolute steering angle than middle-aged participants while performing this task (means = 2.55 vs. 3.07 deg for middle-aged and older participants, respectively; $t(57) = -2.927$, $p = 0.005$). The mean absolute roll rate reported in Fig. 5.3 (middle) was also significantly higher for the older participants (means = 1.88 vs. 2.32 deg/s for middle-aged and older participants, respectively; $t(57) = -4.013$, $p < 0.001$). R^2 values between roll rate and steering rate were significantly higher for older participants than for middle-aged participants ($t(57) = -2.405$, $p = 0.019$). Moreover, results showed significant differences between the two age groups in the delay between roll rate and steering rate ($t(57) = 2.827$, $p = 0.006$), in that the steering rate lagged the roll rate less among older participants compared to the middle-aged participants (Table 5.5).

The results of Task 2 clearly show that the average steering angle decreased with increasing speed (Fig. 5.4 top). No significant differences were found between the two age groups in steering and bicycle roll measures in Task 2 (Table 5.5).

Table 5.5. Means and standard deviations of the dependent measures for the three tasks for middle-aged and older participants on the conventional bicycle and the pedelec (measures are averaged across time) and results of the *t* tests for steering and bicycle roll (the two bicycle types were aggregated).

	Conventional bicycle Middle-aged participants		Pedelec Middle-aged participants		Conventional bicycle Older participants		Pedelec Older participants		Middle-aged vs. older Both bicycle types		
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	<i>t</i> (df)	<i>p</i>	η^2
Steering performance											
T1: Mean absolute steering angle (deg) (5 to 20 s)	2.50	0.98	2.60	0.69	3.07	0.71	3.07	0.86	-2.927 (57)	0.005	0.131
T2: Mean absolute steering angle (deg) (0 to 16 km/h)	6.76	3.90	7.04	4.78	6.00	2.97	6.15	2.89	0.972 (66)	0.335	0.017
T3: Mean absolute steering angle (deg) (3 s before head start - head start)	1.83	0.48	1.80	0.53	2.18	0.57	2.49	1.52	-3.388 (50)	0.001	0.187
T3: Mean absolute steering angle (deg) (head start - head end)	3.34	2.15	2.85	1.67	4.23	2.24	4.18	2.36	-2.327 (50)	0.024	0.098
Bicycle roll											
T1: Mean absolute roll rate (deg/s) (5 to 20 s)	1.97	0.43	1.79	0.31	2.48	0.54	2.16	0.56	-4.013 (57)	<0.001	0.220
T2: Mean absolute roll rate (deg/s) (0 to 16 km/h)	7.04	2.84	5.71	2.01	6.79	1.79	6.08	1.81	-0.132 (56)	0.895	0.000
T3: Mean absolute roll rate (deg/s) (3 s before head start - head start)	3.81	0.95	3.80	1.24	3.68	0.99	4.36	1.35	-0.852 (50)	0.398	0.014
T3: Mean absolute roll rate (deg/s) (head start - head end)	5.27	2.19	4.95	1.85	6.06	1.89	6.79	2.47	-2.802 (50)	0.007	0.136
T1: Time delay between steering rate and roll rate (s)	0.16	0.04	0.14	0.04	0.13	0.03	0.12	0.03	2.827 (57)	0.006	0.123
T1: <i>R</i> ² between steering rate and roll rate (0 - 1)	0.34	0.14	0.41	0.13	0.45	0.11	0.44	0.12	-2.405 (57)	0.019	0.092
Speed											
T1: Mean speed (km/h) (5 to 20 s)	7.60	0.66	7.42	0.37	7.93	0.85	7.62	0.71	-	-	-
T3: Mean speed (km/h) (3 s before head start - head start)	12.81	1.27	13.74	2.15	11.91	1.46	13.20	1.94	-	-	-
T3: Mean speed (km/h) (head start - head end)	12.18	1.72	13.09	2.54	11.58	1.60	12.52	2.29	-	-	-
Time											
T2: Time to reach 16 km/h (s)	4.28	1.17	3.79	1.03	6.10	1.93	4.26	1.50	-	-	-
T3: Time head start - head end (s)	2.14	0.72	2.10	0.70	2.40	0.61	2.36	0.76	-	-	-

Notes. T1 – Task 1: Low-speed cycling, T2 – Task 2: Accelerating, T3 – Task 3: Shoulder check; *p* values < .05 are in boldface. A positive *t* statistic means that middle-aged cyclists had a higher score than older cyclists and a negative *t* statistic means that middle-aged cyclists had a lower score than older cyclists. '-' indicates that *t* test was not performed; see Table 6 for ANOVAs regarding the speed and time measures.

Table 5.6. Summary of ANOVA results regarding bicycle type, age group, and interaction between bicycle type and age group.

	Within-subjects effect				Between-subject effect				Interaction effect			
	Bicycle type				Age group				Bicycle type*Age group			
	<i>F</i> (<i>df1</i> , <i>df2</i>)	<i>p</i>	<i>MSE</i>	η^2	<i>F</i> (<i>df1</i> , <i>df2</i>)	<i>p</i>	<i>MSE</i>	η^2	<i>F</i> (<i>df1</i> , <i>df2</i>)	<i>p</i>	η^2	
Speed												
T1: Mean speed (km/h) (5 to 20 s)	7.97 (1, 57)	0.007	0.22	0.122	3.09 (1, 57)	0.084	0.67	0.051	0.50 (1, 57)	0.484	0.008	
T3: Mean speed (km/h) (3 s before head start - head start)	20.49 (1, 50)	<0.001	1.53	0.288	2.93 (1, 50)	0.093	4.56	0.055	0.55 (1, 50)	0.460	0.008	
T3: Mean speed (km/h) (head start - head end)	11.01 (1, 50)	0.002	1.99	0.180	1.32 (1, 50)	0.255	6.71	0.026	0.00 (1, 50)	0.946	0.000	
Time												
T2: Time to reach 16 km/h (s)	52.82 (1, 56)	<0.001	0.75	0.418	11.21 (1, 56)	0.001	3.37	0.167	17.41 (1, 56)	<0.001	0.138	
T3: Time head start - head end (s)	0.12 (1, 50)	0.727	0.27	0.002	2.40 (1, 50)	0.127	0.72	0.046	0.00 (1, 50)	0.972	0.000	

Notes. T1 – Task 1: Low-speed cycling, T2 – Task 2: Accelerating, T3 – Task 3: Shoulder check, *p* values < .05 are in boldface.

Regarding Task 3 the mean absolute steering angle was small (about 2–3 deg) prior to head turn but grew substantially during the head turn for both participant groups riding on two types of bicycles (Fig. 5.5 top). This trend after the head turn was also observed for the mean absolute bicycle roll rate (Fig. 5.5 middle). Participants' age had a significant effect on the mean absolute steering angle in both subtasks of Task 3 ($t(50) = -3.388, p = 0.001$ and $t(50) = -2.327, p = 0.024$, for subtasks '3 s before head start – head start' and 'head start – head end', respectively) and on the mean absolute roll rate in the 'head start – head end' subtask ($t(50) = -2.802, p = 0.007$). Thus, older participants used more steering control than middle-aged participants when indicating direction by hand and performing the shoulder check (Table 5.5).

As can be seen in the top of Figs. 5.3–5.5, the absolute steering angle on both bicycle types was high at the start of each exercise (i.e., when speed was low) and decreased with increasing speed/time. Another noteworthy observation was that both middle-aged and older cyclists showed large individual differences in steering performance (see *SDs* in Table 5.5).

5.3.3.2. Speed and time

As shown in Fig. 5.3 (bottom), cyclists slightly exceeded the instructed speed of 7 km/h in Task 1 on both bicycles during the whole task. The analysis of variance revealed a significant effect of bicycle type (means = 7.77 vs. 7.52 km/h for conventional bicycle and pedelec, respectively; $F(1,57) = 7.97, p = 0.007$), but the effect of age was not statistically significant. Interaction effects 'bicycle type x age' during Task 1 were not significant (Table 5.6).

Fig. 5.4 (bottom) clearly shows that when riding on the pedelec, participants accelerated faster compared to when riding on the conventional bicycle. Furthermore, middle-aged participants accelerated faster than older participants. Note that older participants on the pedelec reached the target speed after approximately the same number of seconds as middle-aged participants did on the conventional bicycle (means = 4.26 vs. 4.28 s, respectively). The analysis of variance showed a significant effect of bicycle type ($F(1,56) = 52.82, p < 0.001$) and age ($F(1,56) = 11.21, p = 0.001$), as well as an interaction between bicycle type and age ($F(1,56) = 17.41, p < 0.001$). This interaction effect indicates that older participants benefited more from using a pedelec than middle-aged participants in terms of accelerating as quickly as possible to 16 km/h (Fig. 5.4 bottom).

The analysis of speed in Task 3 showed there was a significant effect of bicycle type ($F(1,50) = 20.49, p < 0.001$; $F(1,50) = 11.01, p = 0.002$, for subtasks '3 s before head start – head start' and 'head start – head end', respectively). Participants rode faster on the pedelec than on the conventional bicycle while indicating direction by hand and shoulder check (Fig. 5.5 bottom). In addition to the analysis of speed in Task 3, the time when participants turned their head was examined, but no significant effect of bicycle type nor age was found. As in Task 1, interaction effects 'bicycle type x age' during Task 3 were not significant (Table 5.6).

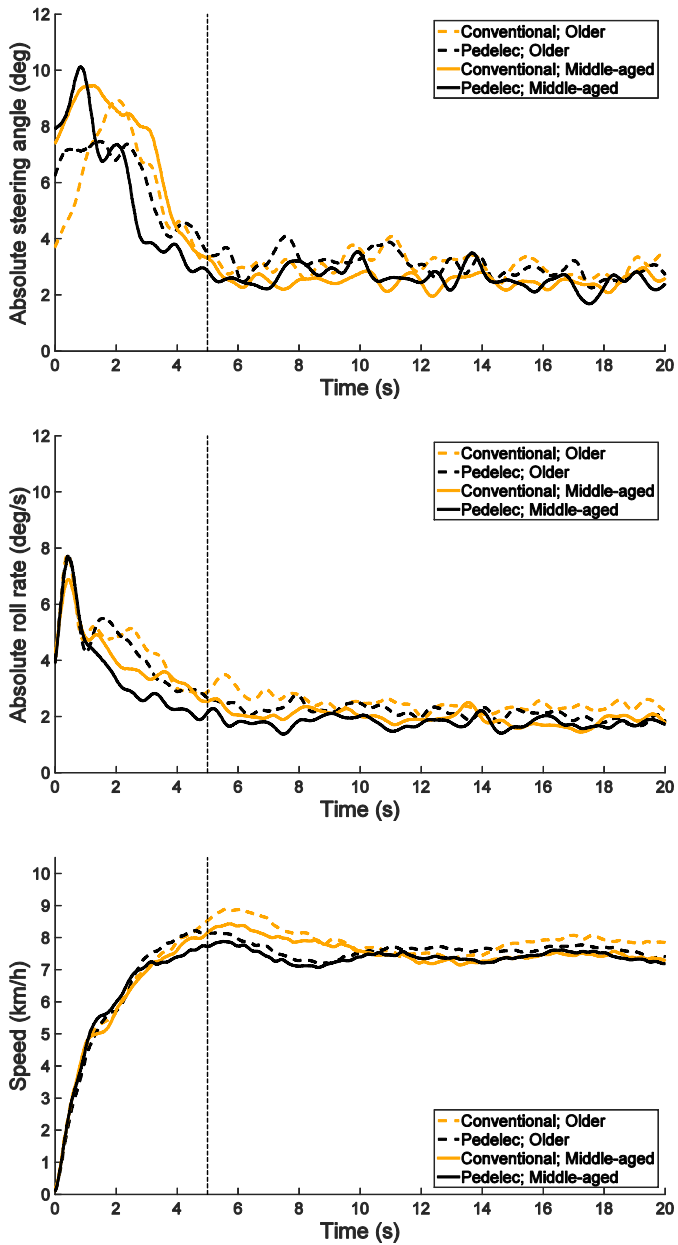


Fig. 5.3. Mean absolute steering angle (top), mean absolute roll rate (middle), and mean speed (bottom) during low speed cycling (Task 1). The vertical dashed line indicates 5 seconds from the start, which is the moment from which data were used in the statistical analyses. For improved clarity of the figures, the absolute steering angle and the absolute roll rate were filtered with an additional low-pass (1 Hz cut-off frequency) forward and reverse filter.

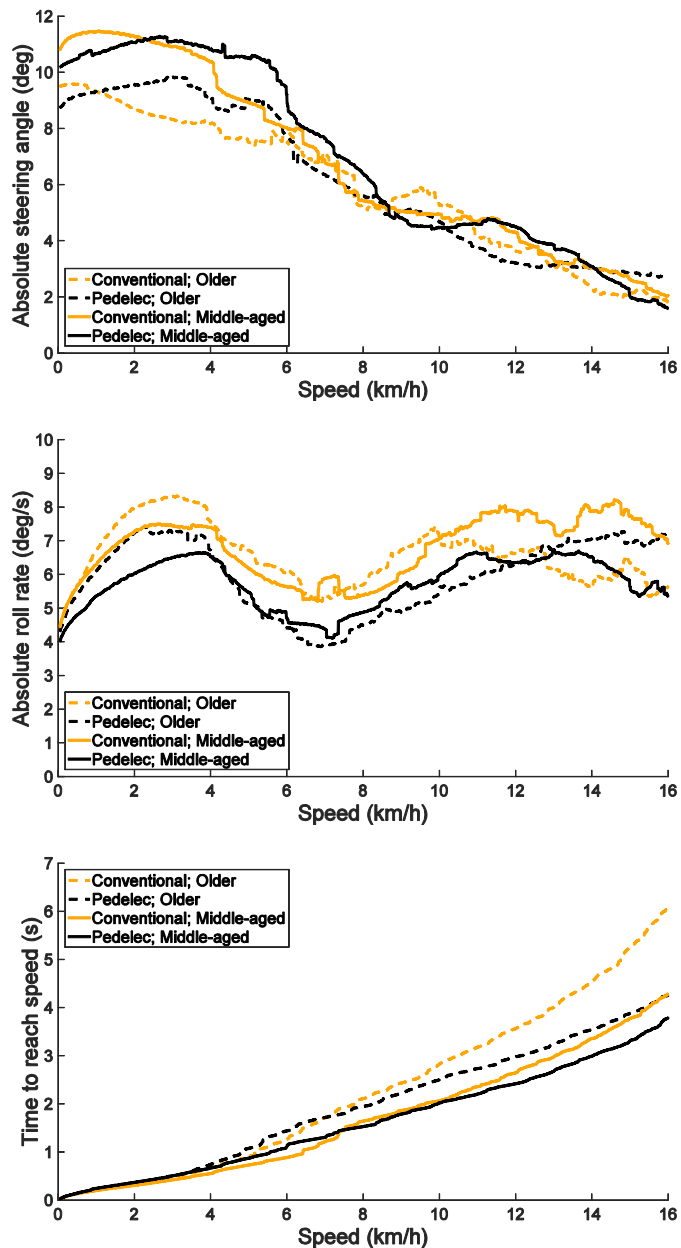


Fig. 5.4. Mean absolute steering angle (top), mean absolute roll rate (middle), and mean time to reach threshold speed (bottom) during the acceleration task (Task 2). For improved clarity of the figures, the absolute steering angle and the absolute roll rate were filtered with an additional low-pass (1 Hz cut-off frequency) forward and reverse filter.

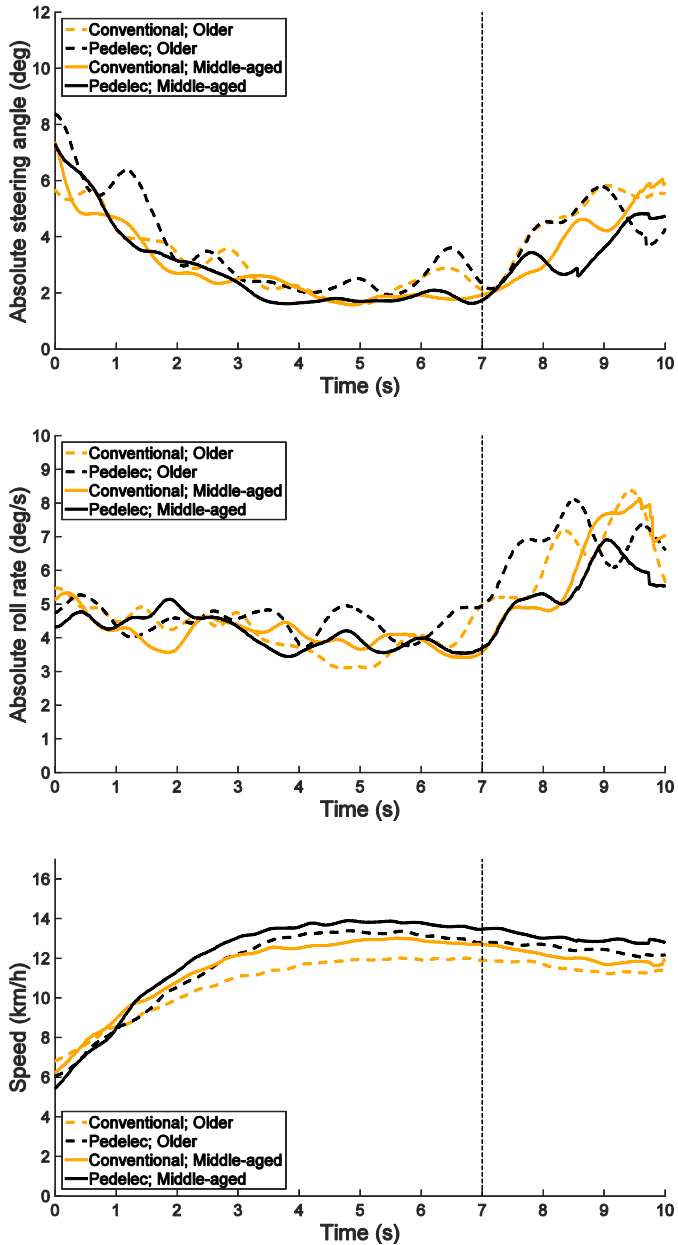


Fig. 5.5. Mean absolute steering angle (top), mean absolute roll rate (middle), and mean speed (bottom) during the shoulder check task (Task 3). The moment when participants started to turn their head is indicated by the vertical dashed line. For improved clarity of the figures, the absolute steering angle and the absolute roll rate were filtered with an additional low-pass (1 Hz cut-off frequency) forward and reverse filter.

5.3.4. Correlations between background variables, self-reported skills, and actual performance

As shown in Table 5.7, correlations between self-reported skills (measured by the CSI) and actual cycling performance were rather weak and out of 30 correlations, only two were statistically significant. Specifically, participants who had better safety skills scores accelerated more slowly to the target speed of 16 km/h in Task 2 and had a shorter delay between roll rate and steering rate.

Table 5.7. Correlations among all variables (performance measures were averaged across both types of bicycles).

	1	2	3	4	5	6	7	8
1 Gender (1 = female, 2 = male)	-							
2 Age (years)	0.11	-						
3 Kilometers per week	-0.02	-0.22	-					
4 Biking frequency	-0.36**	-0.35**	0.55***	-				
5 Grip strength (N)	0.66***	-0.37**	0.10	-0.03	-			
6 Reaction time (ms)	-0.14	0.20	-0.22	0.02	-0.20	-		
7 CSI: Motor-tactical skills ^a	-0.20	-0.11	-0.14	0.10	-0.16	0.13	-	
8 CSI: Safety skills ^a	0.08	-0.22	-0.06	-0.03	0.17	-0.02	0.51***	-
9 T1: Mean absolute steering angle (deg) (5 to 20 s)	0.09	0.50***	-0.08	-0.14	-0.11	0.10	-0.17	-0.04
10 T1: Mean absolute roll rate (deg/s) (5 to 20 s)	0.18	0.53***	-0.24	-0.29*	-0.05	0.11	-0.11	-0.15
11 T1: Time delay between roll rate and steering rate (s)	-0.23	-0.34**	0.08	0.28*	-0.06	-0.01	0.25	0.27*
12 T1: R ² between steering rate and roll rate (0-1)	0.40**	0.27*	-0.13	-0.17	0.28*	0.00	-0.21	-0.07
13 T2: Mean absolute steering angle (deg) (0 to 16 km/h)	-0.20	0.08	-0.25	-0.14	-0.08	0.15	0.25	0.05
14 T2: Mean absolute roll rate (deg/s) (0 to 16 km/h)	-0.28*	0.05	-0.05	0.03	-0.41**	-0.12	-0.16	-0.22
15 T3: Mean absolute steering angle (deg) (3 s before head start - head start)	0.10	0.53***	-0.21	-0.34*	-0.18	0.32*	-0.11	-0.15
16 T3: Mean absolute roll rate (deg/s) (3 s before head start - head start)	0.02	0.29*	0.06	-0.08	-0.11	0.24	-0.17	-0.09
17 T3: Mean absolute steering angle (deg) (head start - head end)	0.10	0.38**	-0.34*	-0.25	0.00	0.29*	-0.12	-0.08
18 T3: Mean absolute roll rate (deg/s) (head start - head end)	0.13	0.33*	-0.11	-0.06	0.00	0.16	-0.22	-0.18
19 T1: Mean speed (km/h) (5 to 20 s)	0.02	0.20	0.00	-0.05	-0.03	0.00	-0.02	-0.08
20 T3: Mean speed (km/h) (3 s before head start - head start)	0.04	-0.20	0.11	0.11	0.09	-0.16	-0.06	0.01
21 T3: Mean speed (km/h) (head start - head end)	-0.01	-0.17	0.23	0.19	-0.02	-0.11	-0.06	-0.04
22 T2: Time to reach 16 km/h (s)	-0.46***	0.37**	-0.11	0.01	-0.65***	0.37**	0.15	-0.27**
23 T3: Time head start - head end (s)	0.27	0.38**	-0.38**	-0.27	0.11	0.14	0.12	0.14

Notes. CSI – Cycling Skill Inventory, T1 – Task 1: Low-speed cycling, T2 – Task 2: Accelerating, T3 – Task 3: Shoulder check. Sample size varied between 51 and 61 for the 140 pairs of variables listed. ^a Participants rated each item from 1 (*much better*) to 5 (*much worse*); * $p < .05$, ** $p < .01$, *** $p < .001$

The correlation analysis also showed that high grip strength was positively related to (1) being male, (2) being young, and (3) a shorter time to reach the threshold speed of 16 km/h in Task 2. Reaction time positively correlated with total time in Task 2. Furthermore, females took longer to reach the target speed of 16 km/h in Task 2. Age was positively correlated with the mean absolute steering angle and mean absolute roll rate in Tasks 1 and 3, time measures in Tasks 2 and 3, and negatively with the time delay between roll rate and steering rate. Weekly distance traveled was inversely related to mean absolute steering angle when participants were looking over shoulder in Task 3 and also to the total time of this subtask (i.e., head start – head end). This suggests that more experienced participants performed the shoulder check subtask in a shorter time and with lower mean steering angles.

5.4. Discussion

With the increasing use of new vehicle technologies such as pedelecs, it is imperative to determine how the vehicle technologies themselves and the characteristics of their users contribute to traffic safety. The popularity of pedelecs – particularly among older people who are considered as the most vulnerable group of road users due to their physical frailty (OECD, 2001) – led us to examine how age is associated with self-reported cycling skills and actual cycling performance.

Overall, the results of the low-speed cycling and shoulder check tasks showed that older cyclists maintain balance by additional steer and roll motions. On the contrary, no statistically significant differences in balancing the bicycles between two age groups were found while accelerating as fast as possible to a typical cruising speed.

It is interesting that older riders exhibited higher R^2 values and shorter time delays between roll rate and steering rate compared to middle-aged riders during low-speed cycling (Task 1). Similar results were found by Cain (2013) when comparing experienced and inexperienced cyclists. Specifically, in one of his experiments, Cain (2013) found that the R^2 s between bicycle roll rate and steer rate were lower for cyclists than for non-cyclists. As mentioned previously, riders stabilize a bicycle by means of two main control inputs: steering and upper-body lean (Kooijman & Schwab, 2013). In addition, external perturbations such as crosswind can have a substantial effect on the dynamics of the bicycle (Schwab et al., 2016). Thus, the determinants of the relationship between roll rate and steering rate are complex. We believe it is possible that riders of different experience and age groups adopted a different posture and different types of upper-body movements while cycling, giving rise to the observed differences in the time delay and R^2 measures.

The older cyclists experienced difficulties at the operational level, when indicating direction with the left hand and when looking over the shoulder (Task 3). As mentioned above, the 23 cyclists (out of the 31 older participants) who were included in statistical analysis performed significantly more corrections per time unit to stabilize a bicycle than middle-aged participants. Older cyclists may benefit from technology fitted on the bicycle that makes the head-turn task easier for them (see Engbers et al., 2014, for a recently developed technical solution: a rear-view assistant).

Consistent with previous research (e.g., Kallman et al., 1990; Shaffer & Harrison, 2007), older participants had a lower grip strength and longer reaction times than middle-aged participants. The results also showed a negative relationship between grip strength and the time to reach 16 km/h. Moreover, we found a positive association between reaction time versus the time to reach the threshold speed (Task 2) and the mean absolute steering angle during performing the shoulder check (Task 3). In other words, a reaction time measurement obtained in stationary non-cycling conditions was predictive of several measures of cycling performance. However, it should be noted that grip strength and reaction time are not necessarily specific causal factors of cycling skill, but are also manifestations of general age-related physical and cognitive fitness (e.g., Der & Deary, 2006). It is useful to point out that several previous studies have used a different approach, whereby reaction times were measured during cycling, either using a visual detection task (Vlakveld et al., 2015) or an auditory detection task (Wierda & Brookhuis, 1991). These studies have found that both very young cyclists (6–8 years; Wierda and Brookhuis, 1991) and older cyclists (65 or older; Vlakveld et al., 2015) have higher reaction times than middle-aged cyclists, pointing to a reduced spare mental capacity while cycling (Vlakveld et al., 2015; Wierda & Brookhuis, 1991).

Our field experiment confirms earlier research (Cain, 2013; Kooijman & Schwab, 2013) that the mean absolute steering angle was substantially higher at the start than after the approximately first 5 s of the ride. These findings may have implications for the design of cycle lanes. For instance at intersections where cyclists usually have to stop and start, the lane width may have to be larger in comparison to straight sections when a high speed can be maintained (see Godthelp & Wouters, 1980 for further discussion).

The recorded data shown in Figs. 5.3 and 5.4 (middle) suggest that roll angle rates while cycling at low speed (Task 1) and accelerating (Task 2) were lower for the pedelec than for the conventional bicycle. This can be explained by pedaling which is performed with greater physical exertion on the conventional bicycle. This tentative explanation can be used as a basis for future research to more clearly demonstrate the interaction between bicycle types, pedaling, and roll motion.

The second research question in this study examined whether participants on a pedelec adopt different speeds than the same participants on a conventional bicycle. When participants cycled at their own pace (Task 3), they adopted a higher speed on the pedelec than on the conventional bicycle, which is consistent with previous research (Dozza et al., 2016; Schleinitz et al., 2017; Vlakveld et al., 2015). Moreover, when instructed to accelerate as quickly as possible (Task 2), participants reached the 16 km/h threshold speed sooner on the pedelec than on the conventional bicycle, an effect that was most pronounced among the older cyclists. A comparison of the accelerations on the parking lot with accelerations from standstill at traffic lights (during the 30-min rides that took place before the present parking lot exercises) showed that whereas there was a significant effect of bicycle type up to 6 km/h on the parking lot, the effect was not significant at the traffic lights (Platteel et al., 2015). When accelerating up to 10 km/h (data analyzed between 6 and 10 km/h) participants gained the threshold speed more

quickly on the pedelec than on the conventional bicycle regardless of the traffic context. The emerging conclusion here appears to be that cyclists can reach the desired speed faster on the pedelec, but in actual traffic cyclists benefit from the assistance provided by the electric motor to accelerate with less physical exertion rather than to accelerate faster (see also Schleinitz et al., 2017).

An interesting finding was that older participants on the pedelec reached the threshold speed in approximately the same amount of time as middle-aged participants did on the conventional bicycle. Furthermore, the average speed of older people on the pedelec was approximately the same as the speed of the middle-aged cyclists on the conventional bicycle during the shoulder check. These results are in line with those obtained during the 30-min rides ridden on both bicycles before parking lot exercises (Vlakveld et al., 2015) and with the German Naturalistic Cycling Study (Schleinitz et al., 2017) in which the low speed among older participants was interpreted as a compensation for reduced functioning (i.e., cyclists reduce their speed in situations involving high physical or mental demands; see also Fuller, 2005).

Consistent with literature on car driving, participants on average rated themselves to be better than an average cyclist of the same age. Specifically, across all 17 items of the CSI, in 45.7% of the cases participants rated themselves “better” or “much better” than the average cyclist, while only 4.5% rated themselves as “worse” and “much worse”. Such a finding is commonly regarded as an illusion, because (if participants are representative of the population) it is extremely unlikely that most of drivers or riders are truly more skilled than the average driver/rider (Taylor & Brown, 1988). For methodological issues and explanations referring to distortions in social judgments and cognitive illusions which provide possible explanations for these findings, see Sundström (2008).

The third research question examined participants' own assessment of motor-tactical and safety skills and its correlation with actual cycling performance. Correlations between self-reported skills (measured by the CSI) and actual performance were weak and mostly not statistically significant. In addition to imprecisions of self-assessments, a possible explanation for the fairly low association between the questionnaire responses and actual cycling measures is that the CSI included a variety of skills (i.e., motor skills, perceptual skills, emotional skills, safety skills) whereas during the exercises on the parking lot the focus was on motor skills.

The fourth research question investigated whether participants believe their performance during field test was better on the conventional bicycle than on the pedelec, or vice versa. Participants believed that they could accelerate from standstill better on the pedelec than on the conventional bicycle, which concurs with the results of Task 2. In general, participants did not perceive a large difference in control and maneuvering between the two bicycle types.

Several limitations should be considered when interpreting the results of the present study. First, self-selection bias should be kept in mind when interpreting the results. The cyclists voluntarily participating in this study may have been more fit than an average

older person. Thus, this study may have under-sampled the very old participants who are unable to ride a conventional bicycle. The average daily distance cycled by our participants was two to three times higher than the distance cycled by the average Dutch person (see CBS, 2015), which can be explained by the fact that only people who cycled regularly participated in our experiment. Second, all tasks were performed in a safe environment without other road users. As we discussed, cyclists may perform differently when conducting exercises on a parking lot compared to when riding in actual traffic (see Platteel et al., 2015). Third, despite the use of high quality sensors, we did not compare the bicycles on steer and roll rate measures by means of statistical tests because of small differences in the accuracy of these sensors. Consequently, the results do not provide a comprehensive insight into how the greater mass of a pedelec and available cycling power affects the cyclist's performance. Although we have no reason to suppose that any systematic bias exists in the present results, it is possible that small differences in calibration, play, or mounting of the sensors distort the results, especially when considering that high-frequency vibrations are omnipresent in cycling data. Note that this limitation only concerns comparisons *between* bicycles; the assessment of effects *within* bicycles (i.e., age effects, correlations with self-reports) is not susceptible to this problem. Fourth, the research design of this study does not permit drawing conclusions on whether cyclists overestimate or underestimate themselves. Future research can shed more light on this topic by relating cyclists' self-assessment to reference values in standardized cycling exercises and an examiner's assessment.

5.5. Conclusions and recommendations

The results of the present study showed that cyclists aged 65 and over maintained balance by additional steer and roll motions during low-speed cycling at 7 km/h and looking over the shoulder, as compared to middle-aged cyclists. Moreover, our results showed that pedelecs allowed older cyclists in particular to accelerate quickly to cruising speed. Consistent with literature on car driving, cyclists rated themselves to be better than average cyclists of the same age. Additionally, self-reported motor-tactical and safety skills were not strongly associated with measures of actual cycling performance. The age-related differences in cycling performance may have to be taken into account when designing interventions to support cycling safety. However, the challenge remains to determine whether a pedelec affects the risk of crashing as compared to conventional bicycles, and whether any increase in bicycle crashes should be attributed to population aging and/or to the bicycle characteristics. Future field studies are needed in the actual traffic environment to investigate how task demands at the tactical level (i.e., traffic situations) influence the task execution at the operational level (e.g., keeping balance, accelerating).

References

- Cain, S. M. (2013). *An experimental investigation of human/bicycle dynamics and rider skill in children and adults*. Doctoral dissertation. Ann Arbor, MI: University of Michigan.
- CBS (2015). *The Netherlands: Cycling country (Factsheet)*. The Hague: CBS Statistics Netherlands.
- Conway, J. M., & Huffcutt, A. I. (2003). A review and evaluation of exploratory factor analysis practices in organizational research. *Organizational Research Methods*, 6, 147–168.
- Daniels, E. B., Zajkowski, M. M., & Drury, C. G. (1976). Bicycle riding performance. In *Proceedings of the human factors and ergonomics society annual meeting* (Vol. 20, pp. 410–414). MD, USA: College Park.
- De Groot-Mesken, J., & Commandeur, J. (2014). *Hoe goed weten oudere fietsers wat ze kunnen? Een veldexperiment met gewone en elektrische fietsen [How capable are elderly cyclists of assessing their skills? A field experiment with conventional and electric bicycles]* (Report No. R-2014-19). The Hague: SWOV Institute for Road Safety Research.
- De Winter, J. C. F., & Dodou, D. (2012). Factor recovery by principal axis factoring and maximum likelihood factor analysis as a function of factor pattern and sample size. *Journal of Applied Statistics*, 39, 695–710.
- Der, G., & Deary, I. J. (2006). Age and sex differences in reaction time in adulthood: Results from the United Kingdom health and lifestyle survey. *Psychology and Aging*, 21, 62–73.
- Dodds, R.M., Syddall, H.E., Cooper, R., Benzeval, M., Deary, I.J., Dennison, E.M., Der, G., Gale, C.R., Inskip, H.M., Jagger, C. and Kirkwood, T.B., (2014). Grip strength across the life course: Normative data from twelve British studies. *PLOS One*, 9, e113637.
- Dozza, M., Bianchi Piccinini, G. F., & Werneke, J. (2016). Using naturalistic data to assess e-cyclist behavior. *Transportation Research Part F: Traffic Psychology and Behaviour*, 41, 217–226.
- Drury, C. G., & Daniels, E. B. (1980). Predicting bicycle riding performance under controlled conditions. *Journal of Safety Research*, 12, 86–95.
- Elander, J., West, R., & French, D. (1993). Behavioral correlates of individual differences in road-traffic crash risk: An examination of methods and findings. *Psychological Bulletin*, 113, 279–294.
- Engbers, C., Dubbeldam, R., Schaake, L., De Hair, S., De Goede, M., & Buurke, J. (2014). Supporting elderly cyclist with rear-view assistance. In *Proceedings of the International Cycling Safety Conference 2014*, Gothenburg, Sweden.
- Fonda, B., Sarabon, N., & Li, F. X. (2017). Bicycle rider control skills: Expertise and assessment. *Journal of Sports Sciences*, 35, 1383–1391.
- Fuller, R. (2005). Towards a general theory of driver behaviour. *Accident Analysis & Prevention*, 37, 461–472.

- Fyhri, A., & Fearnley, N. (2015). Effects of e-bikes on bicycle use and mode share. *Transportation Research Part D: Transport and Environment*, 36, 45–52.
- GDV (2014). *Compact accident research: Traffic safety of electric bicycles (No. 46)*. Berlin: GDV German Insurance Association.
- Godthelp, J., & Wouters, P. I. J. (1980). Course holding by cyclists and moped riders. *Applied Ergonomics*, 11, 227–235.
- Horrey, W. J., Lesch, M. F., Mitsopoulos-Rubens, E., & Lee, J. D. (2015). Calibration of skill and judgment in driving: Development of a conceptual framework and the implications for road safety. *Accident Analysis & Prevention*, 76, 25–33.
- Jensen, A. R. (2006). *Clocking the mind: Mental chronometry and individual differences*. Amsterdam: Elsevier.
- Kallman, D. A., Plato, C. C., & Tobin, J. D. (1990). The role of muscle loss in the age-related decline of grip strength: Cross-sectional and longitudinal perspectives. *Journal of Gerontology*, 45, M82–M88.
- Keskinen, E., & Hernetkoski, K. (2011). Driver education and training. In B. E. Porter (Ed.), *Handbook of Traffic Psychology* (pp. 403–422). London: Academic Press.
- Kooijman, J. D. G., Schwab, A. L., & Moore, J. K. (2009). Some observations on human control of a bicycle. In *Proceedings of the ASME 2009 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference* (pp. 2021–2028), San Diego, CA, USA.
- Kooijman, J. D. G., & Schwab, A. L. (2013). A review on bicycle and motorcycle rider control with a perspective on handling qualities. *Vehicle System Dynamics*, 51, 1722–1764.
- Kuiken, M., & Twisk, D. (2001). *Safe driving and the training of calibration (Report No. R-2001-29)*. Leidschendam: SWOV Institute for Road Safety Research.
- Lajunen, T., & Summala, H. (1995). Driving experience, personality, and skill and safety-motive dimensions in drivers' self-assessments. *Personality and Individual Differences*, 19, 307–318.
- MacArthur, J., & Kobel, N. (2015). Regulations of e-bikes in the United States: A policy review. In *Transportation Research Board 94th Annual Meeting*, Washington DC, USA, No. 15-4235.
- Michon, J. A. (1985). A critical view of driver behavior models: What do we know, what should we do? In L. Evans & R. C. Schwing (Eds.), *Human behavior and traffic safety* (pp. 485–524). New York: Plenum Press.
- Moore, J. K., Kooijman, J. D. G., Schwab, A. L., & Hubbard, M. (2011). Rider motion identification during normal bicycling by means of principal component analysis. *Multibody System Dynamics*, 25, 225–244.
- Mortimer, R. G., Domas, P. A., & Dewar, R. E. (1976). The relationship of bicycle manoeuvrability to handlebar configuration. *Applied Ergonomics*, 7, 213–219.
- OECD (2001). *Ageing and transport: Mobility needs and safety issues*. Paris: OECD Publishing.

- OECD/International Transport Forum (2013). *Cycling, health and safety*. Paris: OECD Publishing/ITF.
- Papoutsis, S., Martinolli, L., Braun, C. T., & Exadaktylos, A. K. (2014). E-bike injuries: Experience from an urban emergency department – A retrospective study from Switzerland (Article ID 850236). *Emergency Medicine International*.
- Platteel, S., Twisk, D., & Lovegrove, G. (2015). Pedelec and instability of the elderly during mounting manoeuvres. In *Proceedings of the 4th International Cycling Safety Conference*. Germany: Hannover.
- Rice, R. S., & Roland, R. D. (1970). *An evaluation of the performance and handling qualities of bicycles (Technical Report VJ-2888-K)*. Buffalo, NY: Cornell Aeronautical Laboratory.
- Schepers, J. P., Fishman, E., Den Hertog, P., Klein Wolt, K., & Schwab, A. L. (2014). The safety of electrically assisted bicycles compared to classic bicycles. *Accident Analysis & Prevention*, 73, 174–180.
- Schleinitz, K., Petzoldt, T., Franke-Bartholdt, L., Krems, J., & Gehlert, T. (2017). The German naturalistic cycling study – Comparing cycling speed of riders of different e-bikes and conventional bicycles. *Safety Science*, 92, 290–297.
- Schwab, A. L., Kooijman, J. D. G., & Meijaard, J. P. (2008). Some recent developments in bicycle dynamics and control. In *Proceedings of the 4th European Conference on Structural Control (4ECSC)*, St. Petersburg, Russia.
- Schwab, A. L., Dialynas, G., & Happee, R. (2016). The effect of crosswind on the dynamics and control of bicycle. In *Proceedings of the 4th Joint International Conference on Multibody System Dynamics*, Montréal, Canada.
- Shaffer, S. W., & Harrison, A. L. (2007). Aging of the somatosensory system: A translational perspective. *Physical Therapy*, 87, 193–207.
- Sundström, A. (2008). Self-assessment of driving skill – a review from a measurement perspective. *Transportation Research Part F: Traffic Psychology and Behaviour*, 11, 1–9.
- SWOV (2013). *Cyclists (SWOV Fact sheet)*. Leidschendam: SWOV Institute for Road Safety Research.
- Taylor, S. E., & Brown, J. D. (1988). Illusion and well-being: A social psychological perspective on mental health. *Psychological Bulletin*, 103, 193–210.
- Van Boggelen, O., Van Oijen, J., & Lankhuijzen, R. (2013). *Feiten over de elektrische fiets [Facts about the electrically assisted bicycle]*. Utrecht: Fietsberaad.
- Vlakveld, W. P., Twisk, D., Christoph, M., Boele, M., Sikkema, R., Remya, R., & Schwab, A. L. (2015). Speed choice and mental workload of elderly cyclists on ebikes in simple and complex traffic situations: A field experiment. *Accident Analysis & Prevention*, 74, 97–106.
- Weber, T., Scaramuzza, G., & Schmitt, K.-U. (2014). Evaluation of e-bike accidents in Switzerland. *Accident Analysis & Prevention*, 73, 47–52.
- Wierda, M., & Brookhuis, K. A. (1991). Analysis of cycling skill: A cognitive approach. *Applied Cognitive Psychology*, 5, 113–122.

Wolf, A., & Seebauer, S. (2014). Technology adoption of electric bicycles: A survey among early adopters. *Transportation Research Part A: Policy and Practice*, 69, 196–211.

CHAPTER 6

CYCLING SKILL INVENTORY: ASSESSMENT OF MOTOR-TACTICAL SKILLS AND SAFETY MOTIVES

It is well established within the traffic psychology literature that a distinction can be made between driving skill and driving style. The majority of self-report questionnaires have been developed for car drivers, whereas only limited knowledge exists on the riding skill and style of cyclists. Individual differences in cycling skills need to be understood in order to apply targeted interventions. This study reports on a psychometric analysis of the Cycling Skill Inventory (CSI), a self-report questionnaire that asks cyclists to rate themselves from definitely weak to definitely strong on 17 items. Herein, we administered the CSI using an online crowdsourcing method, complemented with respondents who answered the questionnaire using paper and pencil ($n = 1,138$ in total). The results showed that 2 components underlie the item data: motor-tactical skills and safety motives. Correlational analyses indicated that participants with a higher safety motives score were involved in fewer self-reported cycling accidents in the past 3 years. The analysis also confirmed well-established gender differences, with male cyclists having lower safety motives but higher motor-tactical skills than female cyclists. The nomological network of the CSI for cyclists is similar to that of the Driving Skill Inventory for car drivers.

This chapter is based on De Winter et al. (2019). See the published paper for all results.

De Winter, J. C. F., Kováčsová, N., & Hagenzieker, M. P. (2019). Cycling skill inventory: Assessment of motor-tactical skills and safety motives. *Traffic Injury Prevention*, 1–7.

6.1. Introduction

It is well established that a distinction exists between driving skill and driving style. These dimensions arise from self-reports such as the Driving Skill Inventory (DSI), distinguishing between skills and safety motives (Lajunen & Summala, 1995), and the Driver Behaviour Questionnaire, distinguishing between errors and violations (Reason et al. 1990). The majority of questionnaires have been developed for drivers, whereas only limited knowledge exists on the riding skill and style of cyclists. Exceptions are Feenstra et al. (2010), Hezaveh et al. (2018), and Useche et al. (2018), who developed cycling behavior questionnaires, and Martínez-Ruiz et al. (2014), who found that young males are involved in more cycling accidents than older females. The overinvolvement of males in cycling accidents may be because males cycle more often, behave more riskily, and are more likely to commit traffic violations compared to females (Johnson et al., 2011; Useche et al., 2018).

The high number of cycling accidents raises questions about how to improve cycling safety. Road safety improvements can be categorized into 3 main headings: engineering, education, and enforcement (e.g., Learoyd, 1950). In addition to improvements in enforcement and engineering (e.g., cycling gear, helmets, bicycle stability, road infrastructure), cycling behavior needs to be addressed; for example, by means of educational interventions. Thus, it is important to understand to what extent individual differences are associated with accident involvement. Herein, we focus on the Cycling Skill Inventory (CSI), a questionnaire that is derived from the DSI. The CSI was introduced by De Groot-Mesken and Commandeur (2014) and reused by Kováčsová et al. (2016; Chapter 5) in a sample of middle-aged and older cyclists. In this chapter, we aimed to examine components underlying the CSI data, and correlations between CSI scores, age, gender, cycling frequency, and accident involvement, using a large sample of respondents.

6.2. Methods

6.2.1. Participants

A total of 1,138 respondents (63.0% males, mean age = 35.0 years) completed the questionnaire online or using paper and pencil. Respondents who participated online were recruited via CrowdFlower ($n = 962$) and Facebook ($n = 46$). These respondents completed the CSI near the end of a study about cyclists' responses to videos of hazardous traffic situations (Kováčsová et al., 2019; Chapter 3). Crowdsourcing participants became aware of our survey by logging into a channel website; they would see the survey among a list of available crowdsourcing projects. The Facebook participants were recruited via cycling-related Facebook groups in the Netherlands.

The online sample was complemented with paper-and-pencil CSI questionnaires ($n = 130$), which participants completed as part of computer-based hazard perception experiments at the Delft University of Technology, the Netherlands. The CSI was provided in the English language, except for a portion ($n = 71$) of the paper-and-pencil

questionnaires, which were completed in Dutch among middle-aged and older cyclists (Kováčsová et al., 2020; Chapter 7). The studies were approved by the Human Research Ethics Committee of the TU Delft. All participants provided digital or written informed consent.

The 1,138 participants were mostly from the Netherlands ($n = 175$), United States ($n = 157$), Italy ($n = 115$), Venezuela ($n = 112$), Canada ($n = 67$), Serbia ($n = 52$), and the UK ($n = 51$). In this study, all countries and subsamples were pooled.

6.2.2. Instruments

Cycling skills were measured using the CSI (De Groot-Mesken & Commandeur, 2014). The inventory was produced based on the taxonomy of motor and safety skills by selecting items from the DSI (Lajunen & Summala, 1995) that are also relevant to cyclists and by creating several new cycling-related items (Kováčsová et al., 2016; Chapter 5). Participants rated themselves from 1 = definitely weak to 5 = definitely strong on each of the 17 skill-related items (see Table 6.1 for the 17 items).

In addition to the CSI, the following 5 variables were obtained from the questionnaire:

Gender. 1 = female, 2 = male (63.0% males, $n = 1,134$, 4 missing values).

Age. years (mean = 35.0 years, $SD = 12.4$ years, $n = 1,138$).

Cycling distance. About how many kilometers (miles) on average do you cycle per week in the summertime?, on a scale from 1 = 0 km/miles, 2 = 1–5 km (1–3 miles), 3 = 6–10 km (4–6 miles), 4 = 11–30 km (7–18 miles), 5 = 31–60 km (19–37 miles), ..., to 10 = more than 201 km (more than 125 miles; mean = 4.23, $SD = 1.91$, $n = 1,124$, 14 missing values).

Cycling frequency. How often do you cycle in the summertime?, from 1 = *never* to 6 = *every day*. Participants who reported never were excluded a priori, so effectively the responses ranged from 2 = *less than once a month* to 6 = *every day* (mean = 4.19, $SD = 1.14$, $n = 1,133$, 5 missing values). For this item and the previous item, the words *in the summertime* were not used in the paper-and-pencil questionnaires.

Accidents in last 3 years. How many accidents were you involved in as a cyclist during the last 3 years?, on a scale from 0 = 0 to 6 = *more than 5* (mean = 0.49, $SD = 1.05$, $n = 1,131$, 7 missing values). Respondents had the option to answer the checkbox item, "What was the cause of the accident(s)?" From the 299 respondents who reported an accident in the past 3 years, 282 answered the checkbox item. From those 282, 51.4% selected "fall from bicycle," 25.2% "collision with a motor vehicle (car, truck, etc.)," 22.7% "collision with obstacle (curb, pole, etc.)," 19.9% "collision with another cyclist," 11.3% "collision with a pedestrian," 5.7% "collision with a motorbike/moped," and 2.8% "other."

6.2.3. Statistical analysis

The psychometric properties of the CSI were examined by performing several analyses:

- 1) *Descriptive statistics* (means, standard deviations).

- 2) *Principal component analysis*. The decision to retain 2 components was made by visual inspection of the eigenvalues of the correlation matrix, also referred to as the scree plot. The component loadings were obliquely rotated using the Promax procedure with a power of 4 (Hendrickson and White, 1964; Kováčsová et al., 2016; Chapter 5).
- 3) *Bivariate Pearson product-moment correlations* between principal component scores and criterion variables.

6.3. Results

6.3.1. Descriptive statistics

The means and standard deviations of the 17 items are provided in Table 6.1. Participants rated themselves as weakest for the item “cycling when it is slippery” (mean = 2.62 on a scale from 1 to 5) and gave relatively high ratings to themselves (>3.85) for “obeying traffic signals”, “controlling the bicycle”, “adjusting speed to the conditions”, “cycling carefully”, “obeying traffic rules”, and “showing consideration for other road users”.

6.3.2. Principal component analysis with oblique rotation

The scree plot suggested that 2 components should be retained (see published manuscript). The 2-component solution accounted for 46.8% of the variance: 35.5% and 11.3% for components 1 and 2, respectively.

The rotated component loadings are shown in Table 6.1. Tucker’s congruence coefficient was computed between the obliquely rotated component loadings and the obliquely rotated factor loadings shown in Kováčsová et al. (2016; Chapter 5). The congruence coefficient was 0.91, indicating that the results of Kováčsová et al. (2016; Chapter 5) were fairly accurately replicated using a new and larger sample.

The obliquely rotated component loadings suggest that the first component should be interpreted as safety motives and the second component as motor–tactical skills. High loadings (>0.70) on the safety motives component were obtained for (a) “obeying traffic signals”, (b) “avoiding unnecessary risks”, (c) “cycling carefully”, (d) “obeying traffic rules”, and (e) “showing consideration for other road users”. High loadings (>0.50) on the motor–tactical skills component were found for (a) “cycling when it is slippery”, (b) “knowing how to act in particular traffic situations”, (c) “controlling the bicycle”, (d) “sudden braking and/or swerving when needed”, (e) “fast reactions”, (f) “predicting traffic situations ahead”, and (g) “maneuvering smoothly through busy traffic”.

There were a few items (items 4, 6, 8, 9, 14) that loaded (>0.2) on both components (see Table 6.1). These cross-loadings may occur because these items involve both safety motives and motor–tactical skills. For example, recognizing hazards in traffic can be seen as a tactical skill, where more experienced cyclists are expected to perform better, as well as a safety skill, where more considerate and risk-averse cyclists can be expected to perform better.

Table 6.1. Means, standard deviations (SD), and principal component loadings after oblique (Promax) rotation among the 17 items of the Cycling Skill Inventory ($n = 1138$).

No.	Item	Mean	SD	Obliquely rotated loadings	
				Safety motives	Motor-tactical skills
1	Cycling when it is slippery	2.62	1.04	-0.53	0.61
2	Knowing how to act in particular traffic situations	3.56	0.95	-0.09	0.77
3	Obedying traffic signals	3.89	0.99	0.75	-0.01
4	Tolerating other road users' errors calmly	3.51	0.95	0.36	0.21
5	Controlling the bicycle	4.00	0.84	0.16	0.61
6	Adjusting speed to the conditions	3.91	0.90	0.39	0.42
7	Sudden braking and/or swerving when needed	3.57	0.95	-0.09	0.73
8	Staying calm in irritating situations	3.59	0.99	0.32	0.35
9	Recognizing hazards in traffic	3.83	0.87	0.37	0.40
10	Fast reactions	3.76	0.94	0.02	0.71
11	Yielding to somebody else who does not have right of way	3.32	0.98	0.31	0.13
12	Avoiding unnecessary risks	3.81	1.01	0.80	-0.14
13	Cycling carefully	3.91	0.96	0.86	-0.15
14	Predicting traffic situations ahead	3.73	0.89	0.23	0.55
15	Maneuvering smoothly through busy traffic	3.43	0.98	-0.16	0.76
16	Obedying traffic rules	3.87	0.98	0.79	-0.02
17	Showing consideration for other road users	3.89	0.87	0.71	0.12

Table 6.2. Pearson product-moment correlation coefficients between the obliquely rotated component scores of the Cycling Skill Inventory, Gender, Cycling km, Cycling frequency, and Accidents 3Y.

	1	2	3	4	5	6
1 Safety motives	–					
2 Motor-tactical skills	0.51	–				
3 Gender (1 = female, 2 = male)	-0.15	0.08	–			
4 Age (years)	0.19	0.05	-0.16	–		
5 Cycling km	-0.03	0.16	0.10	0.01	–	
6 Cycling frequency	-0.02	0.24	0.00	0.05	0.47	–
7 Accidents 3Y	-0.18	0.00	0.11	-0.18	0.11	0.19

6.3.3. Correlations between principal component scores and criterion variables

As shown in Table 6.2, older participants had a higher safety motives score than younger participants ($r = 0.19$). Furthermore, males had a lower safety motives score than females ($r = -0.15$). Participants with a higher safety motives score reported fewer

cycling accidents in the past 3 years ($r = -0.18$). However, the motor–tactical skills score was not significantly associated with cycling accidents in the past 3 years ($r = 0.00$). Finally, participants who cycled more often (regarding cycling distance and cycling frequency) had higher motor–tactical skills scores ($r = 0.16$ and $r = 0.24$, respectively).

6.4. Discussion

This study administered the CSI among a large sample of respondents ($n = 1,138$) in a diverse range of countries. The results showed that higher safety motives scores are associated with a smaller number of cycling accidents. We also found that males are involved in more cycling accidents than females, an effect that can be attributed to males having lower safety motives and higher cycling exposure than females (see also Lajunen & Summala, 1995; Useche et al., 2018).

In the case of the CSI, method bias may be due to individual attitudes regarding the rating of oneself on a scale from very weak to very strong. That is, some people may be inclined to rate themselves as having strong skills, for a variety of reasons—perhaps because of social desirability or because of high self-esteem—whereas others may be inclined to rate themselves as having relatively weak skills, regardless of the item content. In addition to using statistical corrections for accounting for method bias, as can be seen in the published manuscript, future research could apply procedural remedies. The inclusion of a social desirability scale would be useful for identifying method bias, whereas forced-choice items could remove such bias and improve validity (Nederhof, 1985; Bartram, 2007; Brown & Maydeu-Olivares, 2011). However, perhaps the only convincing remedy against method bias would be to assess correlations between the CSI and objective rather than self-reported accidents.

Some limitations of the present study should be acknowledged. First, we did not assess actual cycling skills (but see Kováčsová et al. (2016; Chapter 5) for correlations between CSI scores and objective skills). Furthermore, it matters whether participants are asked to rate themselves with respect to an average cyclist of the same age, as in Kováčsová et al. (2016), or whether an internal criterion is used, as in the present study (see also Sundström, 2008). The sample itself is also of influence; for example, in Lajunen and Summala (1995), the sample consisted of university students and in Kováčsová et al. (2016) it was middle-aged and older cyclists, whereas in the present study the sample consisted of relatively young crowd-workers, university students, and middle-aged users of electric bicycles. Our pooling of subsamples may conflate between-group differences with individual differences within the same group. In the published manuscript, we provide subgroup analyses for the 4 largest countries and the 3 sampling methods. The component loadings between the subsamples showed a congruence coefficient of about 0.90, indicating that the CSI structure replicates regardless of context. However, there is heterogeneity between the groups. For example, respondents from the Netherlands reported cycling more frequently than respondents from other countries. Meesmann et al. (2018) found that in the Netherlands cycling is a top 3 mode of transport for 51% of people, whereas this number is only 5% for Venezuela, pointing to major

cultural differences. Future research could recruit representative cyclists of a broad age range and use multilevel modeling to separate group differences from individual differences.

6.5. Conclusions and recommendations

We conclude that the pattern of correlations that we observed for the CSI is similar to the pattern of correlations observed for the DSI by Lajunen and Summala (1995). We also showed that safety motives are a predictor of self-reported accident involvement among cyclists. A thorough insight into the skill and safety motive constructs and their relations with accidents may enable better-tailored training and education programs.

Supplementary material

Supplemental material for this chapter is available at <https://doi.org/10.1080/15389588.2019.1639158>, and raw data and scripts are available at <https://doi.org/10.4121/uuid:daec0b0a-17fc-425b-988c-d55c4fae476a>.

References

- Bartram, D. (2007). Increasing validity with forced-choice criterion measurement formats. *International Journal of Selection and Assessment, 15*, 263–272.
- Brown, A., & Maydeu-Olivares, A. (2011). Item response modeling of forced-choice questionnaires. *Educational and Psychological Measurement, 71*, 460–502.
- De Groot-Mesken, J. D., & Commandeur, J. J. F. (2015). *Hoe goed weten oudere fietsers wat ze kunnen?: een veldexperiment met gewone en elektrische fietsen. [How capable are elderly cyclists of assessing their skills? A field experiment with conventional and electric bicycles]* (Report No. R-2014-19). The Hague: SWOV Institute for Road Safety Research.
- Feenstra, H., Ruiter, R. A., & Kok, G. (2010). Social-cognitive correlates of risky adolescent cycling behavior. *BMC Public Health, 10*, 408.
- Hezaveh, A. M., Zavareh, M. F., Cherry, C. R., & Nordfjærn, T. (2018). Errors and violations in relation to bicyclists' crash risks: Development of the Bicycle Rider Behavior Questionnaire (BRBQ). *Journal of Transport & Health, 8*, 289–298.
- Hendrickson, A. E., & White, P. O. (1964). Promax: A quick method for rotation to oblique simple structure. *British Journal of Statistical Psychology, 17*, 65–70.
- Johnson, M., Newstead, S., Charlton, J., & Oxley, J. (2011). Riding through red lights: The rate, characteristics and risk factors of non-compliant urban commuter cyclists. *Accident Analysis & Prevention, 43*, 323–328.
- Kováčsová, N., De Winter, J. C. F., & Hagenzieker, M. P. (2019). What will the car driver do? A video-based questionnaire study on cyclists' anticipation during safety-critical situations. *Journal of Safety Research, 69*, 11–21.
- Kováčsová, N., De Winter, J. C. F., Schwab, A. L., Christoph, M., Twisk, D. A. M., & Hagenzieker, M. P. (2016). Riding performance on a conventional bicycle and a

- pedelec in low speed exercises: Objective and subjective evaluation of middle-aged and older persons. *Transportation Research Part F: Traffic Psychology and Behaviour*, 42, 28–43.
- Kováčsová, N., Vlakveld, W. P., De Winter, J. C. F., & Hagenzieker, M. P. (In press). PC-based hazard anticipation training intervention for experienced cyclists: design and evaluation. *Safety Science*.
- Lajunen, T., & Summala, H. (1995). Driving experience, personality, and skill and safety-motive dimensions in drivers' self-assessments. *Personality and Individual Differences*, 19, 307–318.
- Learoyd, C. G. (1950). The carnage on the roads. *Lancet*, 258, 367–369.
- Martínez-Ruiz, V., Jiménez-Mejías, E., de Dios Luna-del-Castillo, J., García-Martín, M., Jiménez-Moleón, J. J., & Lardelli-Claret, P. (2014). Association of cyclists' age and sex with risk of involvement in a crash before and after adjustment for cycling exposure. *Accident Analysis & Prevention*, 62, 259–267.
- Meesmann, U., Torfs, K., Nguyen, H., & Van den Berghe, W., (2018). *Do we care about road safety? Key findings from the ESRA1 project in 38 countries*. Brussels: Vias Institute, ESRA project.
- Nederhof, A. J. (1985). Methods of coping with social desirability bias: A review. *European Journal of Social Psychology*, 15, 263–280.
- Reason, J., Manstead, A., Stradling, S., Baxter, J., & Campbell, K. (1990). Errors and violations on the roads: a real distinction? *Ergonomics*, 33, 1315–1332.
- Sundström, A. (2008). Self-assessment of driving skill—A review from a measurement perspective. *Transportation Research Part F: Traffic Psychology and Behaviour*, 11, 1–9.
- Useche, S. A., Montoro, L., Tomas, J. M., & Cendales, B. (2018). Validation of the Cycling Behavior Questionnaire: A tool for measuring cyclists' road behaviors. *Transportation Research Part F: Traffic Psychology and Behaviour*, 58, 1021–1030.

CHAPTER 7

PC-BASED HAZARD ANTICIPATION TRAINING INTERVENTION FOR EXPERIENCED CYCLISTS: DESIGN AND EVALUATION

Research shows that the ability to anticipate safety-critical situations is predictive of safe performance in traffic. Thus far, hazard anticipation training has been developed mainly for car drivers. These training programs may not be appropriate for cyclists who are exposed to different types of hazards. This study aimed to develop a PC-based hazard anticipation training for experienced cyclists, and evaluate its short-term effectiveness using hazard anticipation tests. Sixty-six electric bicycle users completed either a hazard anticipation training or a control intervention. The hazard anticipation training consisted of videos divided into two modules (instructions and practice) and was designed using various evidence-based hazard anticipation educational methods such as a 'What happens next?' task, expert commentary, performance feedback, and analogical transfer between hazardous traffic situations. The evaluation of the training showed that cyclists from the training group identified hazards faster compared to the control group cyclists, but no significant difference was found in the number of detected hazards between the two groups. The training had a small positive effect on cyclists' prediction accuracy at safety-critical intersection situations. No effect was found on perceived danger and risk in hazardous traffic situations. Our results suggest that experienced cyclists' hazard anticipation skills can be improved with the developed PC-based training. Future research should evaluate the retention and transfer of learned skills.

Kováčsová, N., Vlakveld, W. P., De Winter, J. C. F., & Hagenzieker, M. P. (2020). PC-based hazard anticipation training intervention for experienced cyclists: Design and evaluation. *Safety Science*, 123, 104561.

7.1. Introduction

Hazard anticipation, defined as “the ability to read the road and anticipate forthcoming events” (McKenna et al., 2006, p. 2), is a crucial skill for safe performance in traffic. So far, the majority of knowledge on hazard anticipation, its acquisition, and its training has been generated for car drivers (Moran et al., 2019). Although the psychological mechanisms of hazard anticipation may be independent of the vehicle one is operating, traffic situations used in training interventions for car drivers may be inappropriate for other types of road users.

Commuting by bicycle is popular in countries such as the Netherlands and Denmark (Wegman et al., 2012), and the promotion of active forms of transportation is expected to further increase the number of cyclists in traffic (Schepers et al., 2014b). Accordingly, there is a significant need to understand which dangerous situations cyclists encounter and whether cyclists can benefit from hazard anticipation training. Recent naturalistic cycling studies indicate that typical cycling hazards are cars, other cyclists, and pedestrians (Dozza et al., 2016; Dozza & Werneke, 2014; Petzoldt et al., 2017). Furthermore, road safety statistics show that about two-thirds of serious cycling crashes involve a motorized vehicle (European Commission, 2018; Gehlert et al., 2018; Schepers et al., 2017). Interactions with car drivers at intersections are regarded as particularly hazardous (Petzoldt et al., 2017).

Cyclists usually acquire their cycling skills during childhood (Colwell & Culverwell, 2002; Rivara & Metrik, 1998). It may, therefore, be expected that adult cyclists have become competent in hazard anticipation through long-term exposure. Experienced road users have mental models of the traffic environment that allow them to predict hazardous situations effectively (Horswill & McKenna, 2004; Underwood, 2007). However, as argued by Horswill et al. (2013), the hazard anticipation skills of experienced road users are often suboptimal. This argument is supported by evidence from car driving research showing that (1) expert drivers score better at hazard anticipation tasks than experienced drivers (Crundall et al., 2003, 2012), (2) experienced drivers still benefit from hazard anticipation training (Horswill et al. 2013, 2015), (3) no ceiling effect in hazard anticipation skill seems to exist (Horswill et al., 2013), and (4) learning through driving experience is a slow process, possibly due to the lack of performance feedback and the rarity of conflict situations (Horswill, 2016).

In line with research findings that hazard anticipation skills are under-developed even in experienced road users (Crundall et al., 2013; Horswill et al., 2010, 2013, 2015), we designed and evaluated a PC-based hazard anticipation training for experienced cyclists using video clips of hazardous situations collected during everyday commuting. A digital hazard anticipation training may represent a suitable alternative to traffic education (cf. Petzoldt et al., 2013) and may be appropriate for reaching road users who do not have to go through a licensing process, such as cyclists. Our evaluation of the hazard anticipation training was conducted among electric bicycle users, who seem more likely to be involved in severe crashes than persons riding a conventional bicycle (Gehlert et al., 2018; Schepers et al., 2014a). Electric bicycles have gained popularity over the last

decades (Fishman & Cherry, 2016). The elevated risk of electric bicycles may be attributable to the decreased physical and cognitive functions of older people, who are frequent e-bike users, especially in the Netherlands and Austria (Van Boggelen et al., 2013; Wolf & Seebauer, 2014). The two questions addressed in this study are as follows:

1. *How should a training program be designed for enhancing experienced cyclists' hazard anticipation?*

We developed a PC-based hazard anticipation training that aimed to improve experienced cyclists' comprehension of the road environment and prediction of what might subsequently happen. The design of the training intervention was assessed using task performance measures, monitoring of cyclists' subjective state, and cyclists' feedback.

2. *How does the training intervention affect cyclists' hazard anticipation skills and perceived risk?*

We expected that the training would improve cyclists' hazard anticipation skills and perception of risk in safety-critical situations. Training effectiveness was assessed by measuring cyclists' hazard detection times, the number of detected hazards, prediction accuracy, and perceived danger and risk.

In Section 7.2, the design of the hazard anticipation training is described. Section 7.3 describes the methods of the evaluation experiment. The results and discussion for the two research questions can be found in Sections 7.4 and 7.5.

7.2. Hazard anticipation training design

7.2.1. Training methods

A variety of hazard anticipation training strategies have been developed, which aim to either teach visual search skills (e.g., McKenna et al., 2006; Meir et al., 2014), identify regions of the roadway where hazards could arise from (e.g., Fisher et al., 2002; Pollatsek et al., 2006), or improve the anticipation of other road users' actions (e.g., Petzoldt et al., 2013; Vlakveld et al., 2011; Wetton et al., 2013).

Hazard anticipation can be explained by the three-level situation awareness (SA) theory (Endsley, 1995). Level 1 SA is the perception of visual elements of the traffic situation, Level 2 SA involves the comprehension of their meaning, and at Level 3 the road user predicts the future status of the traffic situation. While novices may benefit from learning visual scanning strategies to detect important stimuli (Level 1 SA), experienced road users may benefit from learning to translate the detected visual stimuli into a correct prediction of others' future actions (Level 3 SA) (Crundall et al., 2012).

In hazard anticipation training/tests developed for car drivers, the user typically responds to three types of questions that probe SA: "*What is the hazard?*" (Levels 1 and 2 SA), "*Where is the hazard?*" (Levels 1 and 2 SA), and "*What happens next?*" (Level 3 SA) (Crundall, 2016; Jackson et al., 2009; Ventsislavova & Crundall, 2018). The questions are asked after watching footage of a hazardous traffic situation (i.e., the

situation in which a crash is very likely if not anticipated), which cuts to a black screen when a hazard begins to develop. When responding to the questions, the participant has to reflect actively on the answer, which may benefit knowledge retention (Butler et al., 2007). Additionally, with a PC-based training program, it is possible to provide performance feedback (Petzoldt et al., 2013; Ventsislavova & Crundall, 2018), offering insight into one's performance and possibly reducing self-enhancement bias (Horswill et al., 2017). Furthermore, research has shown that an instructional component may be a useful addition to hazard anticipation training (Horswill, 2016). For example, a running commentary in which an expert points out situational cues has shown a positive effect on hazard perception skills and risk-taking behavior (e.g., McKenna et al., 2006; Wetton et al., 2013). Another training approach is to combine expert commentaries with trainee-generated commentaries to encourage active information processing (e.g., Horswill et al., 2013, 2015; Wetton et al., 2013).

We designed a hazard anticipation training for experienced cyclists using various evidence-based methods mentioned above. The training consisted of two modules. Module 1 was an instructional module with expert commentary and the possibility of replaying the hazardous situations, and Module 2 was a practice module in which participants were encouraged to transfer what they have learned in Module 1 to different but conceptually similar hazardous situations. After the video clip of each traffic situation, the participant had to answer two questions "Where is the location of the hazard?" and "What happens next?" using a multiple-choice format. Visual and auditory feedback was provided after answering each question and could be either positive or negative. In Module 1, the active exploration of the hazard was facilitated by the possibility of viewing the video of the same traffic situation three times before revealing the correct answer.

7.2.2. Training program

The training intervention had a linear user flow in which each participant started with a login screen, followed by introduction videos, Module 1, Module 2, and a wrap-up video clip. The introduction videos provided a description of the application and a definition of hazard anticipation skills. After this introduction, the participant completed 16 trials (i.e., 16 different hazardous traffic situations) divided into the two modules. Each module consisted of one practice and seven training situations. Module 1 had to be completed to unlock Module 2.

The traffic situations were presented in the same order for each participant. In each module, each hazardous traffic situation was presented to the participant using four screens (Fig. 7.1):

- 1) *Knowing the traffic environment*

The participant was presented with a top-down view of the traffic environment that would be shown in the video clip later on. The screen showed an arrow indicating the direction in which the cyclist was riding, and a short description of the environment.

2) *Experiencing the traffic situation*

The participant watched a video that was recorded from the perspective of a cyclist in which one of the road users became a hazard. In Module 1, the video clip could be played three times, depending on the correctness of the participant's responses to the questions. During the second and third play, the video clip was occluded 1 s later than during the previous attempt. This means that three occlusion levels for each traffic situation in Module 1 were created (Fig. 7.2). This was based on the presumption that the temporally closer the cyclist is to the hazard, the more relevant visual information is available, resulting in a higher accuracy of the prediction (Farrow et al., 2005). In Module 2, the video clip of the traffic situation could be played only once.

3) *Anticipating the hazard*

As soon as a hazard started to develop, the video was occluded and a question screen appeared. The question screen included a picture of the same street the cyclist saw in the video clip, but without road users. The first task was to answer the question "What is the location of the hazard?" (hereafter abbreviated as 'Where'). The participant could choose from four pictures in which an orange area was shown and described. The second task was to answer the question "What happens next?" (hereafter abbreviated as 'WHN'). Again, the participant saw four pictures, but this time with a silhouette of the hazardous road user, an arrow indicating the future path of this hazardous road user, and a short description of what would happen next. In each case, there was only one correct answer, and there was always a possibility to answer "I do not know". In Module 1, the participant had to respond correctly to the Where question in order for the WHN question to appear. In Module 2, each question screen was shown only once.

4) *Getting an understanding of the traffic situation*

The participant watched a video clip of the entire situation with a commentary. In Module 1, the expert commentary video clip was composed of a top view of the traffic situation with trajectories of potential hazards, followed by a video clip of the entire traffic situation (Fig. 7.1, Screen 4). In Module 2, the expert-trainee commentary video clip was composed of a picture of the hazard and a short video clip of the matched hazard from Module 1. The commentary said for example: "The hazard was a car that turned and had to yield (referring to the hazard in Module 2, Fig. 7.2, bottom left). This hazard developed similarly to the bus driver who turned and did not notice you (referring to Module 1, Fig. 7.2, left). Let's now watch the entire video clip." Next, a video clip of the entire traffic situation was played, which paused when the hazard started to develop. At this point, the participant was asked to produce a self-commentary for approximately 20 s, after which the remaining part of the video clip would be played.

Supplementary material provides a detailed overview of the user flow of the screens in Modules 1 and 2 and the components of the commentary videos.

1. Knowing the traffic environment

- A short description of the environment
- A top view of the environment



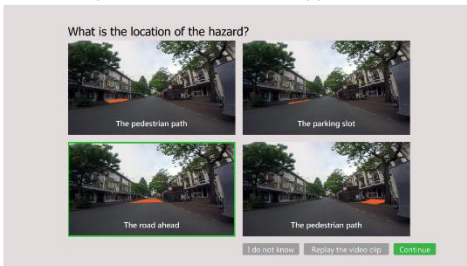
2. Experiencing the traffic situation

- A video clip of the hazardous situation



3. Anticipating the hazard

- A question screen "What is the location of the hazard?"
- A question screen "What happens next?"



4. Getting an understanding of the traffic situation

- A top view of the environment with expert commentary
- Replay of the video clip with expert commentary

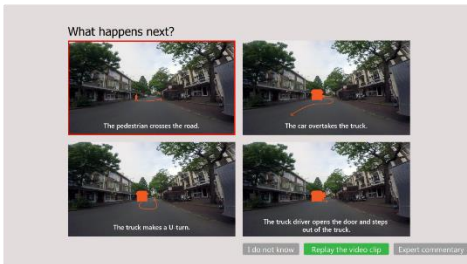
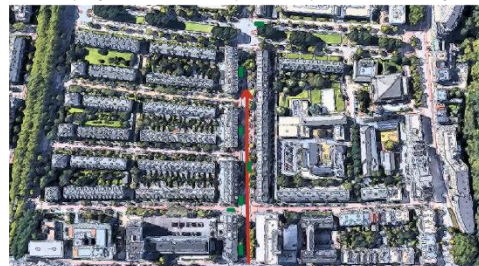


Fig. 7.1. Four screens in Module 1 (Situation 1, Occlusion level 2). The question screen “What is the location of the hazard?” shows an example of positive visual feedback (the green frame around the correct answer). The question screen “What happens next?” shows an example of negative visual feedback (red frame around the incorrect answer). Screens were presented in the Dutch language during the actual experiment.

7.2.3. Performance feedback

Visual and auditory feedback was implemented to the question screens (i.e., Fig. 7.1, Screen 3). If a correct answer was selected, a green frame appeared around the response picture, and positive auditory feedback was provided. The cyclist received

randomly one of nine slightly different positive messages (e.g., “That’s correct!”, “Well done!”). If an incorrect answer was selected, a red frame appeared around the response picture, and negative auditory feedback was triggered. The negative auditory feedback was randomly selected from twelve slightly different short recordings (e.g., “Try again!”, “You didn’t choose the correct answer.”).

The correct answer would be shown (i.e., a green frame around the correct response picture) if the traffic situation had been played three times in Module 1, and always after an incorrect answer in Module 2. Selection of the “I do not know” button did not trigger auditory feedback but triggered a visualization of the correct answer (i.e., a green frame around the correct response picture) if the traffic situation could not be replayed anymore.

7.2.4. Selection of video material

Crundall et al. (2012) showed that the presence of a predictive element (*hazard precursor*) is vital to successful hazard recognition. Acute hazards that appear unexpectedly are unlikely to be anticipated even by experts, and should therefore not be included in hazard anticipation training programs. A further distinction of predictable hazards has been made according to the relationship between precursor and hazard: Vlakveld et al. (2011) distinguished between *overt hazards* (i.e., visible road users whose action can be predicted from their behavior) and *covert hazards* (i.e., invisible road users whose future appearance can be predicted from other visible elements). The terms overt and covert hazards by Vlakveld et al. (2011) correspond to behavioral and environmental hazards as used by Crundall et al. (2012).

Approximately 120 hours of video footage collected during a naturalistic cycling study (Stelling et al., 2017) was analyzed to select hazardous traffic situations. The videos were recorded with GoPro cameras mounted on the head tube of electric or conventional bicycles’ frame. The video data collection took place in the Netherlands during regular commuting and included city cycling (e.g., The Hague, Delft, Haarlem), suburbs, and rural locations.

We initially selected 70 video segments in which cyclists interacted with hazardous road users for inclusion in the training program. The hazard could be either overt (i.e., visible) or covert (i.e., not visible) but the traffic scene had to include a predictive element in order to be eligible for inclusion in the training program. A hazard was defined as a road user on a collision course. Video segments of two types of interactions were selected. In the first type, a road user became a hazard, meaning that this road user crossed the cyclist’s path and the cyclist performed an avoidance maneuver. In the second type, a road user did not materialize into a hazard, possibly because the road user had noticed the approaching cyclist or because of the situation-specific timing of events. The initial selection of 70 video segments was made by the first author. The selection of the final video clips was made by the first two authors by applying the above selection criteria and by observing similarities between matched hazardous situations.

Module 1



Module 2



Fig. 7.2. The three occlusion levels of hazardous situations in Module 1 (top three rows; Left: Situation 2; Right: Situation 6), and the occlusion moment of the matched situations in Module 2 (bottom row).

Table 7.1. A description of the situations in the hazard anticipation training. The matched hazardous situations in Modules 1 and 2 are presented below each other. Note that the hazardous situations in Module 2 followed a different order than presented in this table. See Appendix A for the screenshots of hazards in each traffic situation.

Situation / Module no.	Short description / Hazard type (overt, partially covert, covert)	Potential hazard	Precursor	Location	Bicycle facility
Practice / M1	A car failed to yield to the cyclist while turning right towards a gas station. / Overt	Car	Car indicating the turn and turning	Urban area	Yes
Practice / M2	A car coming from the opposite direction was about to turn to a side street in front of the cyclist. / Overt	Car	Car indicating the turn and turning	Urban area	Yes
1 / M1	Cars overtook a refuse truck, which was parked in the opposite lane. / Partially covert	Cars	Parked truck in contraflow lane with lights on	City center	No
1 / M2	A scooter in the opposite lane was about to perform an avoiding maneuver due to pedestrians who suddenly started to cross the bike path from the left. / Overt	Scooter	A child followed by an adult entering the contraflow lane	Residential area	Yes
2 / M1	A bus failed to yield to the cyclist while turning right at an intersection. / Overt	Bus	Bus indicating the turn; Cyclist in a vehicle blind spot	Urban area	Yes
2 / M2	A car failed to yield to the cyclist while turning right at an intersection. / Overt	Car	Car indicating the turn; Cyclist in a vehicle blind spot	Urban area	Yes
3 / M1	A car pulled out across the bike lane after giving right of way to other cyclists. / Overt	Car	Moving car in front of a bike crossing	University campus	Yes
3 / M2	A car pulled out across the bike lane after giving right of way to cyclists coming from the opposite direction. / Overt	Car	A car stopped before a bike crossing, but the driver's view is obstructed	Residential area	Yes
4 / M1	A distracted pedestrian followed another pedestrian who just crossed the road and was waiting there. / Overt	Pedestrian	Another pedestrian waiting between parked cars	Residential area	No
4 / M2	A child initially hidden behind a parked car was about to cross the road towards the man who was standing on the other side of the road. / Covert	Pedestrian (child)	A man standing between parked cars with a pink school bag	Residential area	No
5 / M1	A cyclist blocked the bike path because a tram was approaching from the opposite direction, and the cyclist could not cross the street. / Overt	Cyclist	Cyclist yielding to an approaching tram	City center	Yes
5 / M2	A group of cyclists blocked the bike path because cars were approaching from the opposite direction, and cyclists could not cross the street. / Overt	Cyclists	Cyclists yielding to the approaching cars	Suburban area	Yes
6 / M1	A pedestrian crossed the road while disappearing behind yielding cars. / Partially covert	Pedestrian	Stopped cars in front of the pedestrian crossing	Suburban area	Yes
6 / M2	A pedestrian walked from the house towards the vehicle while disappearing behind a parked car. / Partially covert	Pedestrian	Car blocking the road with lights on and open trunk	City center	No
7 / M1	A car coming from the right initiated a left turn while being partially hindered by a parked vehicle and vegetation. / Partially covert	Car	Partially blind right bend	Residential area	No
7 / M2	A car coming from the right approached an intersection while being partially hindered by a parked vehicle and vegetation. / Partially covert	Car	Partially blind right bend	Residential area	No

The following selection criteria were further applied: (1) the video was captured during daylight with clear weather conditions, (2) hazard precursors were present, (3) a hazard or precursor was visible for at least 3 s, (4) a minimum of two traffic situations (matched situations) exhibiting similarities between the precursor and the hazard. Regarding the similarities between matched situations, we considered the locations of the precursors and hazards (e.g., a cyclist blocked the bike path because a tram was approaching from the opposite direction vs. a group of cyclists blocked the bike path because cars were approaching from the opposite direction), relationship between precursor and hazard (e.g., a pedestrian crossed the road while disappearing behind yielding cars vs. a pedestrian walked from a house towards the vehicle while disappearing behind a parked car), and behavior of the hazardous road user (e.g., a bus failed to yield to the cyclist while turning right vs. a car failed to yield to the cyclist while turning right).

The relationship between the hazards in the matched situations concerned the application of a strategy of hazard anticipation in Module 1 to a new hazardous situation in Module 2. Sixteen traffic situations (11 taken on an e-bike and 5 on a conventional bike) were selected for our training (see Table 7.1). The hazards in Module 1 situations always developed such that it provided the participant with feedback about what happened next; some of the hazards included in Module 2 (i.e., Situations 1, 4, and 7) did not develop.

7.2.5. Software and materials development

The training program was written in C++ using the cross-platform software Qt. The application ran on a desktop computer. The VLC media player was embedded in the software to play video clips and provide auditory feedback. The interface was designed to allow easy identification of tasks that had to be completed, and short texts were used. This design allowed users with low computer literacy to navigate through the application. User input and time spent on each screen were logged to a text file.

The audio/video material was edited using Audacity and Adobe Premiere Pro CC 2017 and stored with a resolution of 1920 x 1080 pixels at a frame rate of 60 fps. The schematic drawings (i.e., location areas and silhouettes of the hazardous road users) and short text descriptions were created using Adobe Illustrator. The audio from video clips of hazardous traffic situations was removed due to the protection of personal data in Stelling et al. (2017).

7.2.6. Pilot testing

Six one-to-one sessions with traffic safety researchers and two group sessions with seven cyclists per session were conducted to pilot the prototype of the software. The pilot participants independently completed the hazard anticipation training from beginning to end. During the group sessions, only Module 1 was used because of the impracticality of providing self-generated commentaries in a group setting. The one-to-one sessions followed the format of a think-aloud protocol, whereas the participants in the group

sessions were observed by two researchers. Feedback was gathered in the form of questionnaires in the group sessions.

The following changes were implemented after the pilot testing to improve the use and experience with the training software: (1) reducing the duration of the introduction videos, (2) using a neutral voice in the positive and negative feedback recordings, (3) deactivating the response buttons until the moment they have to be used, (4) implementing a reload feature in case a user accidentally closes the program, and (5) correcting confusing drawings of hazard locations and road users.

7.3. Method

7.3.1. Participants

Sixty-six participants (36 females and 30 males) were recruited through flyers and a SWOV participant database. Flyers were distributed during a period of four months (October 2017–January 2018) in bicycle parking facilities in The Hague and Delft and their surroundings. The inclusion criteria stated on the flyer were (a) owning an e-bike and (b) cycling at least three times a week on this e-bike. However, participants using an e-bike on at least a weekly basis were still permitted into the study. The study was approved by the Human Research Ethics Committee of Delft University of Technology (Ethics application no. 262, 2017) and by the SWOV Research Ethics Committee (Ethics application: Hazard anticipation training for e-bikers, 2017).

The participants were split into a training and a control group according to seven characteristics (see Table 7.2) using the Taves' method of minimization (Taves, 1974). The participants assigned to the training group were on average 58.40 years old ($SD = 13.14$, ranging between 26 and 80 years), and participants assigned to the control group were on average 57.82 ($SD = 16.39$, ranging between 19 and 80 years) years old. None of the cyclists had participated in a cycling training course before. Participants' demographic characteristics, cycling, and driving experience are shown in Table 7.2.

7.3.2. Materials

7.3.2.1. Training vs. control group interventions

For the training group (*'training'*), the application described in Section 7.2. was used. Participants completed both training modules in one session without a break. The video clips were played in full-screen mode.

For the control group (*'control'*), a simplified PC-based training course was created without the training methods used in the hazard anticipation training. The control intervention consisted of short clips of traffic scenes taken from a cyclist's point of view on Dutch roads. The control group was provided with 29 video clips divided into three categories: behavior (9 traffic situations), traffic rules (9), and situational awareness (11). Sixteen of these video clips were the same as in the hazard anticipation training. More video clips were added to the control group training than to the hazard anticipation

training group to compensate for the time difference to complete the training programs between the two groups (cf. Horswill et al., 2013).

Table 7.2. Demographic characteristics, cycling, and driving experience of the participants assigned to the training or control group ($n = 66$). The first seven characteristics were used to split participants into the training and control groups.

		Training group	Control group
Gender	Female	18	18
	Male	15	15
Age (years)	≤39	3	5
	40–54	7	6
	55–69	17	14
	≥70	6	8
Eye problems	Chronic	2	2
	Myopia or Hyperopia	18	18
	None	13	13
Weekly cycling mileage (km)	≤30	11	11
	31–90	17	17
	≥91	5	5
Cycling frequency	1–4 days	14	14
	Every day	19	19
Driving license	Yes	30	30
	No	3	3
Yearly driving mileage (km)	0–5,000	16	17
	5,001–20,000	15	14
	≥20,001	2	2
Mean age of starting to cycle		5.0	6.1
Mean number of years of e-bike ownership		4.5	3.3
Bicycle as the primary mode of transportation		27	27
E-bike used more frequently than other types of owned bicycles		29	26
Bicycle accident involvement during the last 3 years		7	6

Each category in the control intervention started with task instructions and a practice video. After each video, a question screen appeared. Questions were related to the behavior of other road users (e.g., “Did the cyclist look left before merging?”), right of way rules (e.g., “Do you have right of way on this crossing?”), and elements of the traffic scene

(e.g., “Which one of these traffic signs was visible before the crossing?”). Depending on the question, the answers were in yes/no or multiple-choice formats. After the participant responded to the question, a short video sequence or a photo from the traffic situation was shown, thus providing the correct answer to the question. This control intervention took 30 min to complete. This intervention was shown to participants in the form of a webpage; the video clips were played in half-screen mode.

All participants sat in front of a 23-in. monitor, and they used a mouse and a keyboard to provide input. Sounds were provided using a headset, or speakers in case a participant wore hearing aids.

7.3.2.2. Evaluation phase (identical for the training and control groups)

7.3.2.2.1. Hazard detection test

Participants' hazard detection performance was measured using 15 short video clips (1 practice and 14 assessment) of real-life cycling in which a hazard developed. Participants were instructed to press the spacebar if they felt that a situation might become dangerous. A maximum of four spacebar presses was recorded per video clip. After each video clip, participants answered the question “How dangerous did you find this situation?” using a 3-point scale ranging from *not dangerous* to *very dangerous*. This test was previously used by Twisk et al. (2018).

Similar to the training and control training programs, the hazard detection test consisted of hazardous situations encountered on Dutch roads. The cyclist taking the video footage was always using a bike lane/path, except for one situation. Regarding the hazards shown in the 14 assessment video clips, four hazards were cars, one was a moped, seven were cyclists or a group of cyclists, and two were pedestrians. Twelve hazards were overt, and two were partially covert (e.g., a car coming from the left was partially hindered by parked vehicles).

7.3.2.2.2. “What will the car driver do next?” questionnaire

A video-based questionnaire was used to examine how well the participants anticipated a driver's right-of-way violation. The questionnaire consisted of one practice and five test video clips taken from a cyclist's perspective on Dutch roads. The five test situations consisted of a safe situation (i.e., approaching car stopped in front of the bike path), three near-miss situations (car crossed the bike path without giving right of way, and the cyclist braked), and one crash situation (approaching car did not give right of way to the cyclist, resulting in a crash). Each video clip was played until 1.14 s before the car entered a bike path, and participants were asked questions about: (1) perceived risk, (2) cyclist's (own) slowing down behavior, (3) prediction of the driver's behavior, and (4) factors that contributed to the prediction of the driver's behavior, (5) priority rules. The ‘what will the car driver do next?’ questionnaire was previously used by Kováčsová et al. (2019).

7.3.2.2.3. Dundee Stress State Questionnaire (DSSQ)

The DSSQ (Matthews et al., 2002) is a 30-item scale for assessing an individual's state before and after a task. The DSSQ distinguishes three dimensions: task engagement, distress, and worry. This questionnaire was used to monitor perceived stress and engagement while completing the training program. Participants were asked to indicate how accurately each of the 30 statements describes their feelings *at the moment* (prior to the training or control intervention) and *while performing the task* (administered two times: after the training or control intervention, and after the evaluation phase) using a 5-point scale ranging from *definitely false* to *definitely true*.

7.3.2.3.4. Evaluation questionnaire

A 9-item evaluation questionnaire was designed to obtain participants' feedback about the training and control interventions. Participants could list positive and negative features of the intervention and indicate what they have learned. They were also asked whether the intervention met their expectations, how well they knew the filmed locations, and how well the video clips resembled situations they normally encounter. The last three items assessed perceived training effects (Horswill et al., 2013). Participants indicated their responses on a 5-point scale ranging *not at all* to *very well / a great extent*. See Fig. 7.5 for the questions and rating scales.

7.3.3. Procedure

Before the test day, participants received a background questionnaire and an informed consent form via email. The experiment was conducted at two locations: SWOV, The Hague (22 cyclists in the training group and 23 in the control group) and TU Delft, Delft (11 cyclists in the training group and 10 in the control group). Participants could pick the testing location according to their convenience. Fig. 7.3 shows the experimental timeline.

A researcher was always present in the experimental room and intervened if the participant was not sure where to click or when self-generated commentaries were not performed. Participants assigned to the control group were offered to complete the hazard anticipation training at the end of the experiment (11 participants completed both interventions). The whole experiment lasted 2 hours for the training group participants and 1.5 hours for the control group participants. Participants were reimbursed with a gift card.

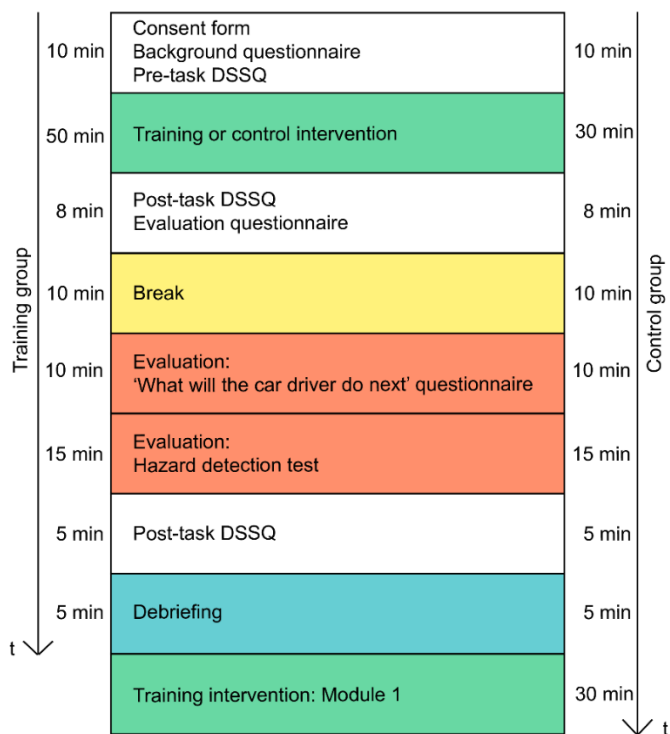


Fig. 7.3. The experimental timeline with durations for the training group (left) and the control group (right).

7.3.4. Measures and analyses

7.3.4.1. Hazard anticipation training measures

The following measures were recorded to monitor training progress and performance:

Time taken to complete the task (min:s). This measure indicates how much time it took to complete Module 1, Module 2, and the entire training.

Time taken to respond correctly (s). This measure indicates how much time participants spent on the 'Where' and 'WHN' questions from the moment the screen appeared until the correct response was selected. In Module 1, the time to respond correctly was calculated as the sum of the time spent on the 'Where' and 'WHN' screens.

Task success rate (%). The rate of the correct responses on the 'Where' and 'WHN' questions. A correct response was scored as 1 and an incorrect response as 0. This score was summed per situation (range 0–2), per question in the module (0–7), and per module (0–14).

Number of video plays to the correct answer (#). This measure described how many video plays of the situation participants used to achieve the correct answer on the 'Where'

and 'WHN' questions in Module 1. Three video plays were available per situation; the first play was mandatory.

7.3.4.2. Evaluation measures and analyses

The hazard detection test consists of 14 hazardous situations (Twisk et al., 2018). A previous evaluation among 30 adult cyclists showed that, for 5 out of 14 hazardous situations, 8 or more participants did not press the spacebar, presumably because they did not consider the traffic situation shown in the video clip to be hazardous (Vlakveld, 2017). For completeness, we compared the two groups using both the 14-hazardous situation version and the reduced 9-hazardous situation version of the test, as previously suggested by Vlakveld, 2017. For our total dataset ($n = 66$), Cronbach's alpha of the detection time scores was .84 if including all 14 situations, and .73 if including the 9 situations. An inspection of the Scree plot (eigenvalues of the correlation matrix) of the detection time scores for the 14 situations showed that a one-factor solution was most appropriate (the first, second, and third eigenvalues were 5.1, 1.7, and 1.3, respectively). The following hazard detection test measures were calculated using both versions of the test:

Hit rate in the interval (%). A time interval was created from the moment the hazard emerged until the moment the hazard was met by the cyclist, that is, when the cyclist arrived at the hazard or the hazard entered the cyclist's future trajectory (see Twisk et al., 2018 for details). The hit rate was defined as the percentage of identified hazards.

Total number of presses (#). The total number of space bar presses in the hazard detection test.

Detection time score. The detection time represents the time between the moment the hazard emerged and the participant's first space bar press within the time interval, with a maximum of 1 (immediate detection) and a minimum of 0 (no detection) (Twisk et al., 2018). In case a participant did not press the space bar during the time interval, the hazard detection score was 0. The detection time score was defined as a sum of these scores.

Mean perceived danger. The perceived danger represents a participant's self-reported danger in viewed hazardous situations. Participants reported perceived danger on a scale from 0 (not dangerous) to 2 (very dangerous).

In addition, *mean perceived risk* measure was calculated for three types of intersection situations: crash, near miss, and safe. Participants reported perceived risk using an item "The situation was risky" which was evaluated on a scale from 1 (strongly disagree) to 7 (strongly agree) when completing "What will the car driver do next?" questionnaire.

Paired sample t tests were conducted to compare participants' performance between the two training modules. Independent samples t tests were used to compare questionnaire and evaluation results between the training and control groups. A 3 x 2 analysis of variance (ANOVA) was performed with the time condition as a within-subject

factor (start, after intervention, end) and intervention group as a between-subjects factor (training vs. control) to examine participants' subjective state (i.e., DSSQ). Bivariate Spearman's rank-order correlations were calculated between hazard detection test measures (data from 9 hazardous situations) and participants' age ($n = 66$).

7.4. Results

7.4.1. Hazard anticipation training

The results for the training progress are shown in Table 7.3 and Fig. 7.4 (details per situation are provided in Supplementary material). Participants completed the training program, on average, in 50 min and 11 s ($SD = 4$ min 41 s). It took approximately two times longer to complete the instructional Module 1 than the practice Module 2 (Table 4.3). Participants took longer to correctly answer 'WHN' questions compared to 'Where' questions.

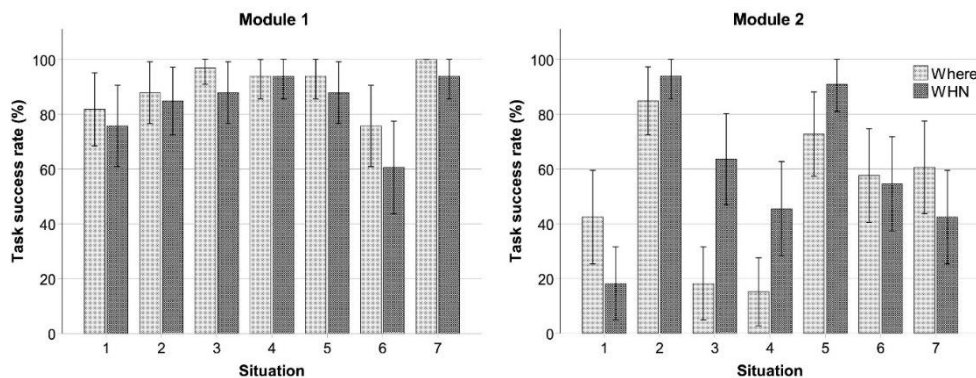


Fig. 7.4. Mean task success rate in 'What is the location of the hazard?' ('Where') and 'What happens next' ('WHN') questions per seven hazardous traffic situations per module. Error bars are ± 1.96 times the standard error of the mean. Note that participants could watch the video clip of each traffic situation three times to answer the questions in Module 1, whereas they watched the traffic video clip only once in Module 2.

In Module 1, participants answered both the 'Where' and 'WHN' questions correctly on the first attempt in 21.2% of cases ($n = 231$), whereas in Module 2, the correctness of responses to the two questions was 37.2% ($n = 231$).

Participants had a higher task success rate in Module 1 than in Module 2 (means = 86.8 and 54.3 for Module 1 and Module 2, respectively). Furthermore, the task success rate was higher for 'Where' questions compared to 'WHN' questions in Module 1, whereas the opposite result was observed in Module 2. This can be explained by the number of video plays in Module 1, which was higher for 'Where' questions (mean = 1.65) and, thus, a lower number of replays was available for 'WHN' questions (mean = 1.45).

Participants' task success rate ranged between 60.0% and 100% for each question and situation in Module 1 (Fig. 7.4 left). The highest task success rate and the lowest number of video plays were observed for Situation 4, in which a distracted pedestrian followed another pedestrian when crossing the road and for Situation 7, in which a partially hidden car coming from right initiated a left turn. The lowest score was observed for Situation 6, in which a pedestrian was crossing the road hindered by the yielding cars. In Module 2 (Fig. 7.4 right), low task success rates were observed for the far transfer Situations 1 and 4, and when a distractor road user was present ('Where' question in Situation 3 and 'WHN' question in Situation 7).

Table 7.3. Means, standard deviations, minima, and maxima of hazard anticipation training measures according to Modules and response questions ($n = 33$).

		Mean	SD	Min	Max
Time taken to complete the task (min:s)					
Module 1		31:22	2:28	26:17	36:35
Module 2		16:31	2:42	13:37	28:36
Hazard anticipation training		50:11	4:41	41:57	65:54
Time taken to respond correctly (s)					
Module 1	Where	14.4	5.7	5.4	27.7
	WHN	16.2	7.2	5.8	31.6
	Where + WHN	30.6	12.0	11.6	59.2
Module 2	Where	7.1	4.0	2.8	17.9
	WHN	7.8	3.1	3.3	15.8
	Where + WHN	12.7	6.3	6.0	31.6
Task success rate (0-100)					
Module 1	Where	90.0	13.1	42.9	100.0
	WHN	83.6	16.8	9.52	100.0
	Where + WHN	86.8	14.4	35.7	100.0
Module 2	Where	50.2	14.8	14.3	71.4
	WHN	58.4	15.7	28.6	85.7
	Where + WHN	54.3	12.0	28.6	78.6
# of video plays to the correct answer (1-3)					
	Where	1.65	0.33	1.14	2.50
	WHN	1.45	0.26	1.00	2.00
	Total	2.07	0.30	1.50	3.00

7.4.2. Evaluation: Cyclists' feedback and subjective state

The control training met participants' expectations better than the hazard perception training, but the effect was not statistically significant (means = 2.67 vs. 3.12 for training and control group, respectively; $t(64) = -1.959$, $d = -0.482$, $p = 0.054$). Frequently mentioned critiques of the hazard anticipation training were related to the video clips and were as follows: poor visibility (e.g., hazards too far), the height of the camera recordings,

speed of the video recordings (or speed of the bicycle), and the lack of the traffic sound. On the other hand, participants liked the realism of the traffic situations (Fig. 7.5), the expert commentary, and the focus on practice.

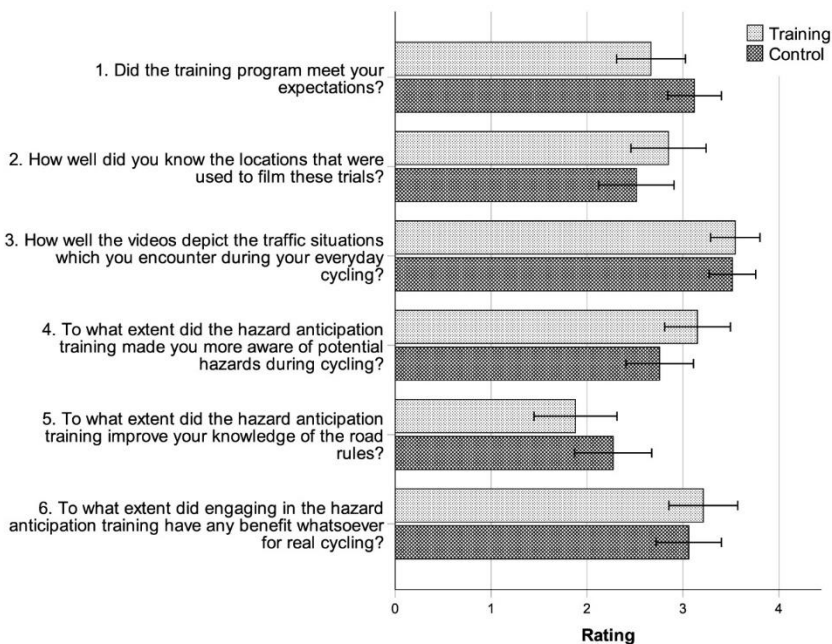


Fig. 7.5. Mean ratings of the six items in the evaluation questionnaire. Error bars are ± 1.96 times the standard error of the mean. Items 1–3 were rated on a scale from 0 = *not at all* to 4 = *very well*, and Items 4–6 were rated from 0 = *not at all* to 4 = *to a great extent*.

Fig. 7.5 shows the mean ratings of the perceived intervention benefits. There were no statistically significant group differences in Items 4–6 between the two groups ($p \geq 0.121$). The analysis of the responses to the open-ended question “what did you learn during the training?” revealed that participants in both groups mentioned they had learned to pay more attention to the traffic. Training participants further mentioned better anticipation, looking further ahead, assessing the situation, and defensive cycling. Control participants reported learning about being alert, looking at the traffic signs, and giving right of way.

The results of the DSSQ showed that participants had high task engagement (Fig. 7.6). Statistically significant differences were observed between the time conditions for the distress ($F(2,116) = 6.640, \eta_p^2 = 0.103, p = 0.002$) and worry subscales ($F(2,110) = 50.518, \eta_p^2 = 0.479, p < 0.001$). Specifically, participants reported higher distress after completing the interventions compared to the Start ($p = 0.059$) and End conditions ($p = 0.002$). Further, participants reported higher worry at the beginning of the experiment

compared to the other two time conditions ($p < 0.001$). No significant differences were observed between the training and control groups ($p \geq 0.222$).

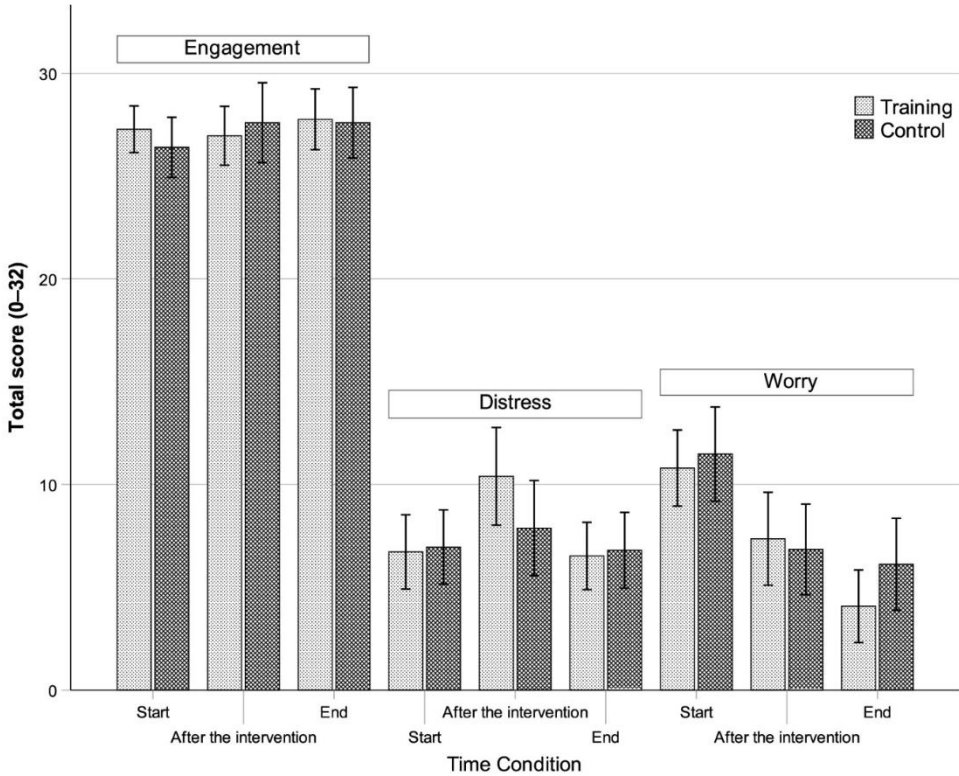


Fig. 7.6. Mean total scores of engagement, distress, and worry scales of the DSSQ administered prior to the intervention (*Start*), *After the intervention*, and at the end of the experiment (*End*) per intervention group. Scores range from 0 to 32. Error bars are ± 1.96 times the standard error of the mean.

7.4.3. Evaluation: Effect of training on hazard anticipation and perceived danger and risk

7.4.3.1. Hazard detection test: Spacebar task

In the hazard detection test consisting of 14 video clips, only 10.6% of participants (5 training vs. 2 control) identified all 14 hazards during the time intervals. When the shorter form of the hazard detection test was used, 25.6% of participants (10 training vs. 7 control) identified all shown hazards during the time intervals. As can be seen in Table 7.4, participants in the training group had a higher hit rate and a higher number of space bar presses compared to the control group. However, these differences were not statistically significant. The training group reacted significantly faster to the hazards compared to the control group ($t(64) = 3.028$, $d = 0.745$, $p = 0.004$).

Correlations between hazard detection test measures and participants' age were significant. More specifically, older participants had a lower hit rate ($\rho = -0.37, p = 0.002$), pressed space bar less frequently ($\rho = -0.38, p = 0.002$), and detected hazards later in time ($\rho = -0.42, p < 0.001$).

Table 7.4. Means and standard deviations of the hazard detection test (top) and perceived risk (bottom) measures administered after the training interventions for the training and control groups, and results of the independent samples *t* tests for these measures. Statistically significant results are depicted in boldface.

	Range	Training		Control		Training vs. Control		
		Mean	SD	Mean	SD	<i>t</i> (df)	<i>d</i>	<i>p</i>
<i>Hazard detection test measures</i>								
HPT9: Hit rate in the interval	0–100	82.2	19.8	75.1	21.2	1.401 (64)	0.345	0.166
HPT14: Hit rate in the interval	0–100	78.8	20.1	69.9	22.7	1.682 (64)	0.414	0.098
HPT9: Total number of presses	0–36	13.27	4.54	11.55	4.68	1.522 (64)	0.375	0.133
HPT14: Total number of presses	0–56	18.97	6.48	16.36	6.88	1.584 (64)	0.390	0.118
HPT9: Detection time score	0–9	4.33	1.46	3.29	1.33	3.028 (64)	0.745	0.004
HPT14: Detection time score	0–14	6.24	2.15	4.73	2.31	2.754 (64)	0.678	0.008
HDT 9: Mean perceived danger	0–2	1.02	0.35	1.09	0.32	-0.817 (64)	-0.201	0.417
HDT 14: Mean perceived danger	0–2	0.89	0.30	0.97	0.32	-1.141 (64)	-0.281	0.258
<i>“What will the car driver do next?” questionnaire: Perceived risk</i>								
Crash: Mean perceived risk	1–7	3.30	1.65	2.50	1.50	2.051 (63)	0.509	0.044
Near miss: Mean perceived risk ^a	1–7	4.64	1.55	4.11	1.49	1.383 (63)	0.343	0.172
Safe: Mean perceived risk	1–7	2.97	1.57	2.56	1.48	1.075 (63)	0.267	0.286

Notes. HDT 9 – Hazard perception test consisting of 9 video clips, HDT 14 – Hazard perception test consisting of 14 video clips.

^a Responses were averaged across the 3 near-miss situations.

7.4.3.2. “What will the car driver do next?” questionnaire: Prediction and slowing-down behavior

Fig. 7.7 shows the percentage of participants who correctly predicted that the car driver would not let the cyclist cross first (i.e., crash and near-miss situations) and the percentage of participants who reported that they would slow down in these situations. The safe situation was used as a control situation.

As can be seen in Fig. 7.7, small differences were observed between the training and control groups in prediction accuracy and in self-reported slowing-down behavior. Participants assigned to the training group were on average more accurate in their predictions and reported to slow down more frequently. Supplementary material provides further details about the participants' reported cues and traffic rules knowledge in the ‘What will the car driver do next?’ questionnaire situations.

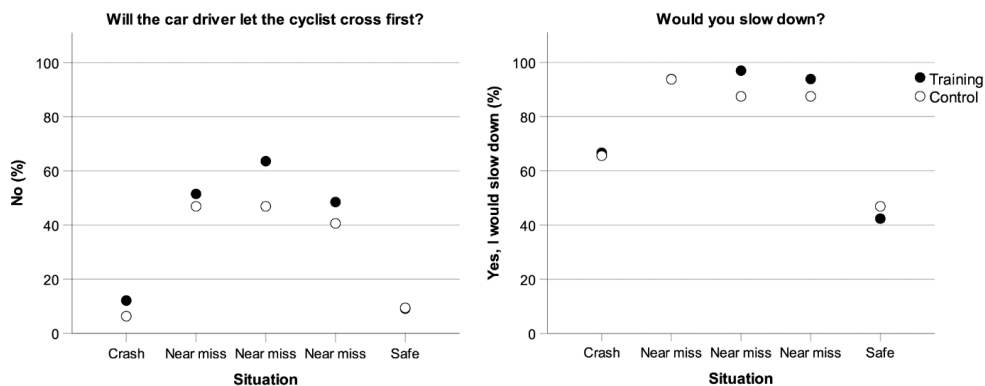


Fig. 7.7. Results for the ‘What will the car driver do next?’ questionnaire. Left: Percentage of participants who reported “no” to the question “Imagine that the cyclist in the video will continue cycling at this speed. Will the car driver let the cyclist cross first?” as a function of the situation and participant group. Right: Percentage of participants who reported “yes, I would slow” down to the question “Imagine that you are the cyclist in the video. Would you slow down?” as a function of the situation and participant group.

7.4.3.3. Perceived danger and risk

As can be seen in Table 7.4 (Hazard detection test measures), there were no significant differences in perceived danger between the two groups in nine everyday hazardous situations ($p = 0.417$). The results for the perceived risk in safety-critical intersection situations showed that training participants perceived higher risk in crash, near-miss, and safe situations compared to the control participants (Table 7.4, “What will the car driver do next?” questionnaire: Perceived risk). The training participants reported significantly higher perceived risk than the control participants in the crash situation ($p = 0.044$).

7.5. Discussion

Previous research has shown that hazard anticipation training can be valuable for enhancing car drivers’ anticipation skills (Horswill, 2016; McDonald et al., 2015). However, knowledge of how to enhance the hazard anticipation skills of cyclists is scarce. Earlier attempts have been made to develop hazard anticipation training for child cyclists (Lehtonen et al., 2017; Zeuwts et al., 2017, 2018). Herein, we developed and evaluated a PC-based hazard anticipation training for experienced adult cyclists.

We evaluated our training program among electric bicycle users, a group that is over-involved in serious crashes as compared to conventional bicycle users (Gehlert et al., 2018; Schepers et al., 2014a). Our participant recruitment strategy resulted in a representative sample of electric bicycle users, consisting of a large share of females and relatively old people (cf. Hendriksen et al., 2008; Van Boggelen et al., 2013). Hazard anticipation skills that involve visual attention, processing of relevant information, and

executive function are likely to decline with age (Anstey et al., 2005; Horswill et al., 2008). Our results showed that older cyclists had a slower reaction time to hazards, and identified fewer hazards during the hazard detection test. However, as shown by Horswill et al. (2010, 2015) among car drivers, experienced older adults' hazard anticipation skills can still be improved by means of training.

The first aim of this study was to evaluate the design of the training program. The self-reports showed that participants did not appreciate our hazard anticipation training any better as compared to the more basic training of the control group. In fact, the results showed a tendency that the expectations of the participants of the control group were better met as compared to the participants of the training group. The participants perceived the expert commentaries in Module 1 as positive, but self-generated commentaries showed a less positive acceptance. The instructional video of Module 2 asked participants to generate commentaries, but participants still had to be reminded by the experimenter to try to generate these commentaries. Consistent with Wetton et al. (2013), we argue that self-generated commentaries may not be a useful addition to the training.

In Module 1, a higher task success rate was observed for 'Where' compared to 'WHN' questions (cf. Gugliotta et al., 2017). In Module 2, however, a higher success rate was observed for 'WHN' than 'Where' questions in the near-transfer situations, a finding that can be attributed to analogical transfer. The presence of a distractor in the video clip, which could also become a hazard, created a confusing element when included in the picture responses. We observed high success rates in Module 2 (suggesting successful transfer between Modules 1 and 2) in two situations: Situation 2 (a bus / a car failed to yield to the cyclists while turning at the intersection) and Situation 5 (a cyclist / a group of cyclist blocked the bike path because another road user was approaching from the opposite direction and the cyclist(s) could not cross the street). Possible reasons for this result could be the similarity of the situations (creating near transfer), situational characteristics that could have led to better remembrance of the hazard, or methodological factors related to the wording of the provided answers.

Future prototypes of the training could take into account the current hazard anticipation skills of the participant by means of pre-testing and a corresponding baseline occlusion level. For example, participants scoring poorly in hazard anticipation could watch the first video clip play until a later moment than participants with high hazard anticipation skills. Although the results showed that on average participants' anticipation skills improved during the training between Module 1 and Module 2, relatively low success scores were observed in Module 2. These low scores may be caused by the training method, the types of hazards, or by the cyclists' suboptimal hazard anticipation skills. Further research is required to set the optimal level of difficulty for the response task taking into account participant's skills.

In the first training prototype, the hazard selection was limited to the video recordings from the recent naturalistic cycling study (Stelling et al., 2017). Regarding cyclist-car driver situations, typical collision scenarios such as blind-spot collisions and situations

where a cyclist is not given right of way by a car driver (Schepers et al., 2011; Summala et al., 1996; Twisk et al., 2013) were included in the training program. The frequency and severity of cyclist-cyclist and cyclist-pedestrian conflict situations are not well known because of the underreporting of these collisions to the authorities (Wegman et al., 2012), which prevents us from drawing conclusions about how representative the situations included in this training program were. Another type of hazards encountered by cyclists are road furniture hazards such as bollards or uneven road surfaces contributing to single-bicycle accidents (Boele-Vos et al., 2017; Schepers & Klein Wolt, 2012). We have not included these types of hazards in our training as they are related to visibility/vision issues than prediction skills (Schepers & Den Brinker, 2011).

The second aim of this study was to evaluate the effect of our training on hazard anticipation skills and perceived risk. The training group detected hazards significantly faster compared to the control group. The group differences in the number of detected hazards were also in favor of the training group, but not statistically significant. These results suggest that our training improved participants' visual skills to detect hazards rapidly (Level 1 SA) or improved participants' processing and prediction strategies (Level 2, 3 SA) to anticipate rapidly that an object develops into a hazard. Overall, our results suggest that PC-based hazard anticipation training enhances the acquisition of situational awareness.

The examination of hazard anticipation skills in safety-critical intersection situations (i.e., near miss, crash), showed small differences between the two groups. One plausible explanation can be that the training targeted rather everyday hazardous situations than severe crash situations. The second explanation can be that safety-critical intersection situations do not include perceivable elements which cyclist can reliably use to predict a driver's right-of-way violation.

As research among car drivers has shown some evidence that individuals who perceive high risk are less likely to show risky behavior in traffic (Deery, 1999), and hazard anticipation training can reduce risk-taking behavior among car drivers (McKenna et al., 2006), the effect of hazard anticipation training on perceived risk and danger was investigated. No significant group differences were found in perceived danger and risk, except for the perceived risk in the 'crash' situation. The perceived danger item and perceived risk items were taken from different previous studies, so the terminology differed. The difference in results between the danger and risk items may have arisen due to chance, or due to the fact that participants' interpretation of the terms risk and danger is not the same. Further, the results suggest that our hazard anticipation training targets primary cognitive skill. The non-significant group differences in perceived risk and the high frequency of self-reported slowing down behavior suggest that the skill training did not cause overconfidence.

The training program in this study was evaluated using objective (e.g., hazard detection times) and subjective (e.g., participants' feedback) measures. The results showed a discrepancy between these two types of evaluation: compared to the control group, our training program tended to yield lower subjective ratings, but significantly

improved hazard detection times. Subjective ratings are vital for judging the acceptability of a training program and for predicting possible disuse in the long term. However, subjective feedback is not informative about actual training effectiveness. The relatively low subjective ratings may be because of usability issues of the software. Future research should examine how a training program should be designed so that participants' expectancies are met.

Several limitations have to be considered when interpreting the results of this study. First, no hazard anticipation test was administered prior to the training. Second, the training was evaluated in the short-term and in a laboratory setting. It is necessary to obtain a better understanding of how our training would affect hazard anticipation skill during real cycling in the longer term, and whether our training is an effective addition to existing bicycle handling and traffic skills interventions for cyclists (e.g., Johnson & Margolis, 2013; Rissel & Watkins, 2014). Third, the training was evaluated among Dutch electric bicycle users, and video clips of traffic situations were captured on the Dutch roads. Future research would be needed to test the training method using traffic situations from other countries, and to evaluate the training among a more diverse sample. The training was developed for cyclists using different types of bicycles (i.e., video footage was collected on conventional and electric bicycles). Future research should evaluate the training program also among conventional cyclists. It can be expected that Dutch conventional bicycle users will have a similar level of experience as participants in this study, but their average age will be lower. A final limitation is that the hazard detection test included hazardous situations only; future research could include a small number of control scenarios without hazard to obtain an index of participants' response bias.

7.6. Conclusions and recommendations

Poor hazard anticipation skill is associated with crash involvement, but limited research exists on how to enhance this skill among cyclists. A PC-based hazard anticipation training has been developed and evaluated to understand whether experienced cyclists benefit from a short intervention. The results showed that the hazard detection time of experienced cyclists was improved with our training intervention. The training consisted of a combination of educational methods, including a 'What happens next?' task, commentary video clips, analogical transfer, and performance feedback. Future research is needed to determine the optimal occlusion points for video clips in training. A longer-term evaluation, as well as an examination of the training effects on real cycling performance, are necessary to determine whether such training contributes to cycling safety.

Compared to car drivers, cyclists do not have to go through a licensing process, which creates challenges regarding how to deliver training programs to this group. Digital media may be a suitable option to make traffic education accessible to cyclists. The self-administration and immediate performance feedback may make the hazard anticipation training an appropriate online educational application.

Supplementary material

Supplementary analyses and materials for this chapter are available at <http://doi.org/10.4121/uuid:df0dcb4f-6064-4712-969e-3cf6fa25a9a2>.

References

- Anstey, K. J., Wood, J., Lord, S., & Walker, J. G. (2005). Cognitive, sensory and physical factors enabling driving safety in older adults. *Clinical Psychology Review*, *25*, 45–65.
- Boele-Vos, M. J., Van Duijvenvoorde, K., Doumen, M. J. A., Duivenvoorden, C. W. A. E., Louwerse, W. J. R., & Davidse, R. J. (2017). Crashes involving cyclists aged 50 and over in the Netherlands: An in-depth study. *Accident Analysis & Prevention*, *105*, 4–10.
- Butler, A. C., Karpicke, J. D., & Roediger III, H. L. (2007). The effect of type and timing of feedback on learning from multiple-choice tests. *Journal of Experimental Psychology: Applied*, *13*, 273–281.
- Colwell, J., & Culverwell, A. (2002). An examination of the relationship between cycle training, cycle accidents, attitudes and cycling behaviour among children. *Ergonomics*, *45*, 640–648.
- Crundall, D. (2016). Hazard prediction discriminates between novice and experienced drivers. *Accident Analysis & Prevention*, *86*, 47–58.
- Crundall, D., Chapman, P., Phelps, N., & Underwood, G. (2003). Eye movements and hazard perception in police pursuit and emergency response driving. *Journal of Experimental Psychology: Applied*, *9*, 163–174.
- Crundall, D., Chapman, P., Trawley, S., Collins, L., Van Loon, E., Andrews, B., & Underwood, G. (2012). Some hazards are more attractive than others: Drivers of varying experience respond differently to different types of hazard. *Accident Analysis & Prevention*, *45*, 600–609.
- Crundall, D., Van Loon, E., Stedmon, A. W., & Crundall, E. (2013). Motorcycling experience and hazard perception. *Accident Analysis & Prevention*, *50*, 456–464.
- Deery, H. A. (1999). Hazard and risk perception among young novice drivers. *Journal of Safety Research*, *30*, 225–236.
- Dozza, M., Piccinini, G. F. B., & Werneke, J. (2016). Using naturalistic data to assess e-cyclist behavior. *Transportation Research Part F: Traffic Psychology and Behaviour*, *41*, 217–226.
- Dozza, M., & Werneke, J. (2014). Introducing naturalistic cycling data: What factors influence bicyclists' safety in the real world? *Transportation Research Part F: Traffic Psychology and Behaviour*, *24*, 83–91.
- Endsley, M. R. (1995). Toward a theory of situation awareness in dynamic systems. *Human Factors*, *37*, 32–64.
- European Commission (2018). *Traffic Safety Basic Facts 2018: Cyclists*.
- Farrow, D., Abernethy, B., & Jackson, R. C. (2005). Probing expert anticipation with the temporal occlusion paradigm: Experimental investigations of some methodological issues. *Motor Control*, *9*, 330–349.

- Fisher, D. L., Laurie, N. E., Glaser, R., Connerney, K., Pollatsek, A., Duffy, S. A., & Brock, J. (2002). Use of a fixed-base driving simulator to evaluate the effects of experience and PC-based risk awareness training on drivers' decisions. *Human Factors*, *44*, 287–302.
- Fishman, E., & Cherry, C. (2016). E-bikes in the mainstream: Reviewing a decade of research. *Transport Reviews*, *36*, 72–91.
- Gehlert, T., Kröling, S., Schreiber, M., & Schleinitz, K. (2018). Accident analysis and comparison of bicycles and pedelecs. In K. Grafl, H. Bunte, K. Dziekan, & H. Haubold (Eds.), *Framing the Third Cycling Century: Bridging the gap between research and practice* (pp. 77–85). Dessau-Roßlau: German Environment Agency.
- Gugliotta, A., Ventsislavova, P., Garcia-Fernandez, P., Peña-Suarez, E., Eisman, E., Crundall, D., & Castro, C. (2017). Are situation awareness and decision-making in driving totally conscious processes? Results of a hazard prediction task. *Transportation Research Part F: Traffic Psychology and Behaviour*, *44*, 168–179.
- Hendriksen, I., Engbers, L., Schrijver, J., Van Gijlswijk, R., Weltevreden, J., & Wiltink, J. (2008). Elektrisch fietsen: Marktonderzoek en verkenning toekomstmogelijkheden [Electric bikes: Market research and exploration of future possibilities]. Leiden: TNO Kwaliteit van Leven.
- Horswill, M. S. (2016). Improving fitness to drive: The case for hazard perception training. *Australian Psychologist*, *51*, 173–181.
- Horswill, M. S., Falconer, E. K., Pachana, N. A., Wetton, M., & Hill, A. (2015). The longer-term effects of a brief hazard perception training intervention in older drivers. *Psychology and Aging*, *30*, 62–67.
- Horswill, M. S., Garth, M., Hill, A., & Watson, M. O. (2017). The effect of performance feedback on drivers' hazard perception ability and self-ratings. *Accident Analysis & Prevention*, *101*, 135–142.
- Horswill, M. S., Kemala, C. N., Wetton, M., Scialfa, C. T., & Pachana, N. A. (2010). Improving older drivers' hazard perception ability. *Psychology and Aging*, *25*, 464–469.
- Horswill, M. S., Marrington, S. A., McCullough, C. M., Wood, J., Pachana, N. A., McWilliam, J., & Raikos, M. K. (2008). The hazard perception ability of older drivers. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, *63*, P212–P218.
- Horswill, M. S., & McKenna, F. P. (2004). Drivers' hazard perception ability: Situation awareness on the road. In S. Banbury & S. Tremblay (Eds.). *A Cognitive Approach to Situation Awareness* (pp. 155–175). Aldershot, UK: Ashgate.
- Horswill, M. S., Taylor, K., Newnam, S., Wetton, M., & Hill, A. (2013). Even highly experienced drivers benefit from a brief hazard perception training intervention. *Accident Analysis & Prevention*, *52*, 100–110.
- Jackson, L., Chapman, P., & Crundall, D. (2009). What happens next? Predicting other road users' behaviour as a function of driving experience and processing time. *Ergonomics*, *52*, 154–164.
- Johnson, R., & Margolis, S. (2013). A review of the effectiveness of adult cycle training in Tower Hamlets, London. *Transport Policy*, *30*, 254–261.
- Kováčsová, N., De Winter, J. C. F., & Hagenzieker, M. P. (2019). What will the car driver do? A video-based questionnaire study on cyclists' anticipation during safety-critical situations. *Journal of Safety Research*, *69*, 11–21.

- Lehtonen, E., Sahlberg, H., Rovamo, E., & Summala, H. (2017). Learning game for training child bicyclists' situation awareness. *Accident Analysis & Prevention, 105*, 72–83.
- Matthews, G., Campbell, S. E., Falconer, S., Joyner, L. A., Huggins, J., Gilliland, K., Grier, R., & Warm, J. S. (2002). Fundamental dimensions of subjective state in performance settings: Task engagement, distress, and worry. *Emotion, 2*, 315–340.
- McDonald, C. C., Goodwin, A. H., Pradhan, A. K., Romoser, M. R., & Williams, A. F. (2015). A review of hazard anticipation training programs for young drivers. *Journal of Adolescent Health, 57*, S15–S23.
- McKenna, F. P., Horswill, M. S., & Alexander, J. L. (2006). Does anticipation training affect drivers' risk taking? *Journal of Experimental Psychology: Applied, 12*, 1–10.
- Meir, A., Borowsky, A., & Oron-Gilad, T. (2014). Formation and evaluation of act and anticipate hazard perception training (AAHPT) intervention for young novice drivers. *Traffic Injury Prevention, 15*, 172–180.
- Moran, C., Bennett, J. M., Prabhakaran, P. (2019). Road user hazard perception tests: A systematic review of current methodologies. *Accident Analysis & Prevention, 129*, 309–333.
- Pollatsek, A., Narayanaan, V., Pradhan, A., & Fisher, D. L. (2006). Using eye movements to evaluate a PC-based risk awareness and perception training program on a driving simulator. *Human Factors, 48*, 447–464.
- Petzoldt, T., Schleinitz, K., Heilmann, S., & Gehlert, T. (2017). Traffic conflicts and their contextual factors when riding conventional vs. electric bicycles. *Transportation Research Part F: Traffic Psychology and Behaviour, 46*, 477–490.
- Petzoldt, T., Weiß, T., Franke, T., Krems, J. F., & Bannert, M. (2013). Can driver education be improved by computer based training of cognitive skills? *Accident Analysis & Prevention, 50*, 1185–1192.
- Rissel, C., & Watkins, G. (2014). Impact on cycling behavior and weight loss of a national cycling skills program (AustCycle) in Australia 2010–2013. *Journal of Transport & Health, 1*, 134–140.
- Rivara, F. P., & Metrik, J. (1998). *Training programs for bicycle safety*. Washington: Washington Traffic Safety Commission, Harborview Injury Prevention and Research Center.
- Schepers, P., & Den Brinker, B. (2011). What do cyclists need to see to avoid single-bicycle crashes? *Ergonomics, 54*, 315–327.
- Schepers, J. P., Fishman, E., Den Hertog, P., Wolt, K. K., & Schwab, A. L. (2014a). The safety of electrically assisted bicycles compared to classic bicycles. *Accident Analysis & Prevention, 73*, 174–180.
- Schepers, P., & Klein Wolt, K. (2012). Single-bicycle crash types and characteristics. *Cycling Research International, 2*, 119–135.
- Schepers, J. P., Kroeze, P. A., Smeets, W., & Wüst, J. C. (2011). Road factors and bicycle–motor vehicle crashes at unsignalized priority intersections. *Accident Analysis & Prevention, 43*, 853–861.
- Schepers, P., Stipdonk, H., Methorst, R., & Olivier, J. (2017). Bicycle fatalities: Trends in crashes with and without motor vehicles in The Netherlands. *Transportation Research Part F: Traffic Psychology and Behaviour, 46*, 491–499.

- Schepers, C. E., Wendel-Vos, G. C. W., Den Broeder, J. M., Van Kempen, E. E. M. M., Van Wesemael, P. J. V., & Schuit, A. J. (2014b). Shifting from car to active transport: A systematic review of the effectiveness of interventions. *Transportation Research Part A: Policy and Practice*, *70*, 264–280.
- Stelling, A., Van Gent, P., De Groot, J., Twisk, D., Vlakveld, W. (2017). Naturalistics cycling study among Dutch commuter cyclists” Comparing speeds on pedelecs, speed-pedelecs and conventional bicycles. In *Road Safety & Simulation International Conference (RSS 2017)*. The Hague, The Netherlands.
- Summala, H., Pasanen, E., Räsänen, M., & Sievänen, J. (1996). Bicycle accidents and drivers' visual search at left and right turns. *Accident Analysis & Prevention*, *28*, 147–153.
- Underwood, G. (2007). Visual attention and the transition from novice to advanced driver. *Ergonomics*, *50*, 1235–1249.
- Taves, D. R. (1974). Minimization: A new method of assigning patients to treatment and control groups. *Clinical Pharmacology & Therapeutics*, *15*, 443–453.
- Twisk, D., Vlakveld, W., Dijkstra, A., Reurings, M., & Wijnen, W. (2013). *From bicycle crashes to measures: Brief overview of what we know and do not know (yet)*. Leidschendam: SWOV Institute for Road Safety Research.
- Twisk, D., Wesseling, S., Vlakveld, W., Vissers, J., Hegeman, G., Hukker, N., Roelofs, E. & Slinger, W. (2018). Higher-order cycling skills among 11- to 13-year-old cyclists and relationships with cycling experience, risky behavior, crashes and self-assessed skill. *Journal of Safety Research*, *67*, 137–143.
- Van Boggelen, O., Van Oijen, J., & Lankhuijzen, R. (2013). *Feiten over de Elektrische Fiets* (Facts about electric bicycles). Utrecht: Fietsberaad.
- Ventsislavova, P., & Crundall, D. (2018). The hazard prediction test: A comparison of free-response and multiple-choice formats. *Safety Science*, *109*, 246–255.
- Vlakveld, W. (2017). *WEVER gevaarherkenningstest voor volwassenen* [WEVER hazard perception test for adults]. Unpublished dataset.
- Vlakveld, W., Romoser, M. R., Mehranian, H., Diete, F., Pollatsek, A., & Fisher, D. L. (2011). Do crashes and near crashes in simulator-based training enhance novice drivers' visual search for latent hazards? *Transportation Research Record*, *2265*, 153–160.
- Wegman, F., Zhang, F., & Dijkstra, A. (2012). How to make more cycling good for road safety? *Accident Analysis & Prevention*, *44*, 19–29.
- Wetton, M. A., Hill, A., & Horswill, M. S. (2013). Are what happens next exercises and self-generated commentaries useful additions to hazard perception training for novice drivers? *Accident Analysis & Prevention*, *54*, 57–66.
- Wolf, A., & Seebauer, S. (2014). Technology adoption of electric bicycles: A survey among early adopters. *Transportation Research Part A: Policy and Practice*, *69*, 196–211.
- Zeuwts, L. H., Cardon, G., Deconinck, F. J., & Lenoir, M. (2018). The efficacy of a brief hazard perception interventional program for child bicyclists to improve perceptive standards. *Accident Analysis & Prevention*, *117*, 449–456.
- Zeuwts, L. H., Vansteenkiste, P., Deconinck, F. J., Cardon, G., & Lenoir, M. (2017). Hazard perception training in young bicyclists improves early detection of risk: A cluster-randomized controlled trial. *Accident Analysis & Prevention*, *108*, 112–121.

CHAPTER 8

DISCUSSION AND CONCLUSIONS

According to the World Health Organization (2018, p. 3) “more than half of the global road traffic deaths are amongst pedestrians, cyclists, and motorcyclists who are still too often neglected in road traffic system design in many countries”. Safety-critical events involving two-wheelers can be attributed to the lack of specific infrastructure features for two-wheelers, the current design of two-wheelers, individual rider characteristics, and poor riding performance (Kruijjer et al., 2012; Penumaka et al., 2014; Schepers and Klein Wolt, 2012). In this dissertation, the cognitive skills and motor performance of two-wheeler users were investigated as contributors to single-vehicle and multi-vehicle accidents.

Traffic safety data shows that a common type of accident involving two-wheeler users is a situation where a car driver drives into their path at an intersection (e.g., Clarke et al., 2007, MAIDS, 2009, Räsänen & Summala, 1998). Although it is the car driver who in the majority of cases violates the formal traffic rules, the cyclist or the motorcyclist may still have been able to prevent the accident by performing an evasive maneuver. According to the situational awareness theory (Endsley, 1995), perception of elements in the environment, comprehension of their meaning, and anticipation of other’s future status are precursors of decision making and carry out an evasive maneuver safely. Accordingly, the **first scope of this dissertation was to investigate cyclists’ hazard anticipation in safety-critical situations and to examine whether hazard anticipation can be enhanced with a short training intervention.**

Not only perceptual errors and false assumptions about others’ future actions but also the failure to perform a satisfactory braking maneuver is a cause of two-wheeler-car accidents. Inadequate motor performance is a contributory factor also to another type of accident: the so-called single-vehicle-loss-of-stability accident. In both types of accidents (i.e., single and multivehicle), the rider has to maneuver his/her vehicle under demanding conditions. **The second scope of this dissertation was to investigate users’ riding performance in critical intersection situations and in low-speed tasks for which handling skills are important.**

The results of this dissertation are summarized and discussed using Michon’s riding task hierarchy (1985; see Fig. 1.2 in Section 1.3.) in the following two subsections.

8.1. Tactical level: cognitive performance

- 1) Which situational and individual factors influence cyclists’ hazard anticipation performance in safety-critical situations at intersections?

Cyclists are more inclined to look at a car that is still on a collision course compared to a car that has already stopped or passed the intersection (even if this car is visually salient and within the field of view of the cyclist). Cyclists use bottom-up and top-down cues to predict what a car driver will do next. Correct predictions of drivers’ right of way violations are associated with cyclists’ perceived high speed and acceleration of the car. Incorrect predictions of drivers’ right of way violations are associated with

perceived low speed and deceleration of the car, as well as with reporting that the cyclist has the right of way. Cyclists' predictions of drivers' actions are more accurate in situations that in reality end up as "near-misses" compared to situations that in reality culminate in "crashes". When the number of cars in the environment increases, cyclists divide their attention between those cars but retain most of their attention to the car that has right of way. Cycling speed has only a small effect on cyclists' eye movements. Gender, age, and cycling experience are not significantly associated with correctly predicting drivers' right of way violations. (see Chapters 2 and 3)

Cyclists' hazard anticipation was investigated in situations where cyclists must have seen the approaching car, i.e., levels 2 and 3 of the situational awareness theory (Endsley, 1995). The results from an eye-tracking study (Chapter 2) indicated that cyclists pay considerable attention to a vehicle on a collision course. The results from a video-based survey study (Chapter 3) showed that cyclists take multiple bottom-up and top-down factors into account for predicting the driver's future action. However, cyclists are able to accurately predict drivers' right of way violations only late even though the cyclist is looking at the approaching car. This finding can be explained either by a late extraction or interpretation of bottom-up cues (i.e., the ambiguity of the available visible cues) or by a late deviation from top-down cues (i.e., incorrectly expecting that the driver will yield, or relying too strongly on formal traffic rules). Additionally, the timing of visual cues is a plausible explanation of why cyclists' predictions are more accurate in near-miss than in crash situations: in near-miss situations, the car drives onto a cyclist's path relatively early.

As cues that indicate that a car driver is not going to yield become manifest only late in time, educational strategies aiming to improve cyclists' hazard anticipation are probably not useful for preventing this particular accident risk. However, increasing cyclists' awareness that a car driver may not have seen the cyclist, and encouraging a 'forgiving' reaction among cyclists, could be viable in training programs. It can be expected that road users will make errors no matter how well the traffic system is designed. Accordingly, the "willingness to anticipate on potentially unsafe actions of another road user and to act in such a way that negative consequences of a potentially unsafe action are prevented or at least limited (i.e., forgiving way)" may contribute to diminishing the risks in traffic (Houtenbos, 2009, p. 5; SWOV, 2010). The effectiveness of such awareness/forgiveness training programs still remains to be investigated. Furthermore, the redesign of infrastructure elements could improve the visibility of others' intentions or eliminate the effect of inappropriate top-down cues (e.g., shared space designs; Hamilton-Baillie, 2008).

A promising technological solution to bicycle-car crashes at intersections may be vehicle-to-vehicle communication systems. The first prototypes of cooperative cyclist-car applications have been designed to warn both the cyclist and the driver in the case of an

imminent threat (Gustafsson et al., 2013; VRUITS EU, 2015), or to warn only one road user (Segata et al., 2017). A limitation of present communication systems is that their design includes only limited knowledge about conditions for triggering a warning (e.g., distance to the intersection, collision probability, the threshold for users' reacting to a warning), which in turn may induce a high false-positive rate. The differences in individual and situational factors between near-miss and crash intersection situations should be addressed when designing these communication systems. Vehicle-to-vehicle communication research is particularly relevant to automated cars, which are able to take over control in the case of an emergency event (VRUITS EU, 2015). Visual external human-machine interfaces are currently tested for car-pedestrian interactions and could be considered as another type of vehicle-to-vehicle communication system for cyclist-car interactions at intersections (e.g., De Clercq et al., 2019).

Lastly, cyclists should contribute to their own safety by using visibility aids such as lights, reflective tires, or fluorescent accessories. Such aids can enhance cyclists' detectability during interactions with car drivers (e.g., Kwan & Mapstone, 2004). The current European regulations enforce reflective devices in the front and rear of the bicycle, as well as pedal and wheels reflectors (European Road Safety Observatory, 2006).

- 2) How does a training intervention affect cyclists' hazard anticipation performance and perceived risk?

A short hazard anticipation training among cyclists does not significantly affect the number of identified hazards, but cyclists who completed the training were faster in identifying hazards compared to a control group. Hazard anticipation training does not affect perceived risk. (see Chapter 7)

The short-term evaluation showed a promising effect of a brief hazard anticipation intervention on cyclists' early hazard detection. Quick and accurate hazard detection offers the cyclist more time for decision making and the execution of appropriate action (Allen et al., 1971; Cumming, 1964). Cyclists may benefit from hazard anticipation training particularly in less critical traffic situations such as when interacting with pedestrians, cyclists, or when a car is traveling at low speed (e.g., pulling out from a parking place). More research is needed to understand which types of hazards can be addressed in hazard anticipation training because not only other road users pose hazards to cyclists but also infrastructure elements such as a bollard, a curb, or uneven road surfaces (Boele-Vos et al., 2017; Schepers & Klein Wolt, 2012).

As cycling education is not mandatory in European countries, hazard anticipation training accessibility through digital media such as a website or mobile phone application can be a suitable option for targeting adult cyclists. Its self-administration, immediate feedback, elicitation of user involvement, and easy application flow are the basic prerequisites of an appropriate online hazard anticipation training.

In this dissertation, only hazard anticipation training was investigated. Education as a traffic safety countermeasure should also address other factors at the strategic, tactical, and operational levels. As mentioned throughout this dissertation, training programs may address cyclists' awareness of drivers' errors and their performance of a forgiving maneuver (SWOV, 2010), precautionary approaching intersection strategies, or knowledge about visibility aids.

8.2. Operational level: motor performance

- 3) How are two-wheeler users' characteristics at the strategic and tactical levels associated with braking performance in safety-critical intersection situations?

Correct predictions of the driver's right of way violation and perceived risk are significant predictors of self-reported slowing down behavior. The more dangerous the situation (safe, near-miss, impending-crash), the more likely cyclists and motorcyclists are to initiate braking. They start to slow-down earlier in near-miss situations than in crash situations. Calculations using the cyclists' deceleration (data from Chapter 5), the estimated cycling speed in the video clips (material in Chapter 3) and participants' responses (data in Chapter 3) showed that cyclists do not have sufficient time to avoid an accident. This result was confirmed in a simulator study showing that motorcycle riders are often unable to avoid a collision with the car in impending-crash conditions. From the three examined visual stimuli (car's speed, car's lateral position, car's indicator), motorcycle riders appear to brake in response to a deviation in the approaching car's heading. (see Chapters 3 and 4)

Car speed was the most frequently reported visual cue in Chapter 3, whereas the simulator study in Chapter 4 showed that braking was not initiated in the majority of cases when a car started to decelerate. These findings point to motorcyclists' difficulty in perceiving a *change* in the speed of the car. Riders appear to initiate braking in response to a deviation in the approaching car's heading. However, this visual cue is present relatively late in time before a crash. Engineering solutions addressing this scenario could either support riders in interpreting the car's speed or adjust road designs so that a car starts to change its heading earlier in time before entering an intersection.

Solely relying on visual cues in the traffic environment is not enough to prevent a collision from happening. The results of this thesis indicate that riders should perform precautionary behavior when approaching an intersection, such as slowing down. For instance, results from a motorcycle simulator study showed that expert motorcycle riders tend to slow down when approaching an uncontrolled intersection (Crundall et al., 2013). It remains to be investigated to what extent precautionary speed reduction would reduce the number of crashes. One recommended measure would be to regulate the speed of

vehicles prior to intersections. Adaptive speed regulations could be applied if a two-wheeler is approaching an uncontrolled intersection from a particular direction.

The recent consensus is that basic motor skills alone are not sufficient for safe performance in traffic (De Winter & Kováčsová, 2016). Although clearly vehicle maneuvering skills (i.e., skills at the operational level) are important determinants of road safety, it is cognitive skills (i.e., at the tactical level) and factors at the highest 'strategic' level that deserve attention in the development of training programs. The current motorcyclists and cyclists educational programs aim to cover mainly safe riding skills, basic bicycle mechanics, traffic knowledge, observed behavior (e.g., indicating direction when turning, riding through traffic lights), and helmet wearing (e.g., Haworth & Mulvihill, 2005; Rissel & Watkins, 2014; Rivara & Metrik 1998; RoSPA, 2001; Swaddiwudhipong et al., 1998). The newly proposed training approach to address two-wheeler rider-car driver conflicts is the focus on the natural coupling of action and perception using real-life mock-up of intersection situations while a rider gets braking performance feedback through a digital interface (Huertas-Leyva et al., 2019). An alternative to instrumented vehicles for a training purpose may be simulators that offer an opportunity to expose trainees to dangerous situations without being physically at risk (De Winter et al., 2012). Nowadays, simulators for cyclists' and motorcyclists' training purposes are practically unavailable (Kováčsová et al., 2015; Twisk et al., 2013).

- 4) How does cycling performance in low-speed tasks differ between riding an electric bicycle and riding a conventional bicycle?

Cyclists accelerate faster and adopt higher speed on the electric bicycle compared to the conventional bicycle. Compared to middle-aged cyclists, older cyclists maintain balance on both conventional and electric bicycles by additional steer and roll motions when cycling at a low speed (approximately 7 km/h) and during shoulder checks. The older cyclists experience difficulties when indicating a direction with their left hand and when looking over the shoulder on both bicycle types. (see Chapter 5)

Cyclists can reach a high speed quicker and cycle faster on an electric bicycle than on a conventional bicycle. The faster acceleration allows cyclists to achieve the speed at which the bicycle stabilizes itself in a shorter time and, thus, they pass the 'risk zone' in which the bicycle is unstable relatively quickly. Recent European field studies have shown that cyclists adopt approximately 3 km/h higher average speed on an electric bicycle compared to a conventional bicycle (Dozza et al., 2016; Schleinitz et al., 2017; Stelling et al., 2017, Stelling-Kończak et al., 2017; Vlakveld et al., 2014). These results, however, apply only to electric bicycles providing support while pedaling up to 25 km/h. Users of another type of electric bicycle, so-called speed pedelecs (Kühn, 2011), adopt average cycling speed of around 30 km/h on bike paths, resulting in a wide range of average cycling speeds (16–30 km/h) of conventional bicycle users, electric bicycle users, and speed pedelec users (Dozza et al., 2016; Schleinitz et al., 2017; Stelling et

al., 2017, Stelling-Kończak et al., 2017; Vlakveld et al., 2014). The differences in cruising speed when sharing bike paths may result in more conflicts due to a higher frequency of overtaking. Further, differences in cycling speeds may contribute to difficulties when interacting with car drivers at intersections, as the car driver has to estimate the approaching bicycle's speed while performing a turn (Schleinitz et al., 2019). A crash countermeasure would be to enforce cycling speeds on bike paths and to remove speed pedelecs to the road in areas where their speed is similar to the speed of motorized traffic (Stelling-Kończak et al., 2017).

The increasing share of electric bicycles has raised the question of how safe they are compared to conventional bicycles. The most recent results suggest that the use of electric bicycles is not associated with a higher risk compared to the use of conventional bicycles (Schepers et al., 2018). However, electric bicycles enable older people to continue cycling longer and more often which can increase the number of serious road injuries (i.e., an exposure effect). When expressed per kilometer traveled by bicycle, older cyclists (60 and older) are the most vulnerable group (SWOV, 2017).

Older cyclists will benefit from bicycle technology which supports them in situations where they have to cycle at low speeds or have to perform additional body movements (e.g., while turning). The first prototype of an electric bicycle that uses steering assist has been tested recently (Schwab et al., 2019). This steer-assist system keeps the bicycle upright and thus maintains the stability of the bicycle from 4 km/h. To address balancing even at speeds lower than 4 km/h, the 'Sofie' bike has been designed (Dubbeldam et al., 2017). This bicycle allows the user to keep the feet on the ground and once the speed goes up, the bicycle saddle automatically rises, providing a more efficient pedaling position for a cyclist (Dubbeldam et al., 2017). This dissertation showed that older cyclists experience difficulties at the operational level when they have to indicate direction by hand while simultaneously turning and look over their shoulder for approaching traffic. Simple solutions such as mirror and indicator lights could assist them in the turning task. A more complex solution is an electronic rear-view assistance system providing information about the traffic approaching from behind through the visual or haptic modalities (Engbers et al., 2016). Lastly, safety measures related to the infrastructure such as separated bicycle facilities or a wide lane width at road sections where the cycling speed is low (e.g., intersections) could contribute to cycling safety for both conventional and electric bicycle users.

Approximately one-fifth of cyclists participating in our studies reported that they had been involved in an accident during the last three years. Current accident data does not contribute to the understanding of contributing factors to less severe bicycle crashes after which a cyclist does not need treatment in the hospital because of their underreporting to the authorities (Wegman et al., 2012). Recently conducted cycling field studies, as well as in-depth accident analyses, are the only sources of knowledge about less severe crashes (e.g., Dozza et al., 2016; Boele-Vos et al., 2017).

8.3. Methodological limitations

Seven different research methods were applied in the studies included in this dissertation: a laboratory experiment using eye-tracking (Chapter 2), a laboratory experiment using a motion-based simulator (Chapter 4), laboratory-based usability testing (Chapter 7), a PC-based laboratory experiment (Chapter 7), a field experiment using instrumented bicycles (Chapter 5), an Internet video-based survey (Chapter 3), and paper-and-pencil questionnaires (Chapters 2, 4, 5, 6, 7). Although triangulation was used in some cases to eliminate drawbacks of a single-method design, several methodological limitations should still be considered when interpreting the results in this dissertation.

Sample: Location diversity. Three studies included in this dissertation were conducted among cyclists living in the Netherlands (Chapters 2, 5, 7). This means that only very experienced cyclists participated in the studies, and also cyclists who are used to cycle in a traffic environment with well-designed cycling infrastructure. The results of these studies may not be generalizable to cities where cycling is emerging. The studies included in Chapters 3 and 6 were conducted among an international sample, but relatively low sample sizes from each country did not allow us to draw strong conclusions on cross-cultural differences (see De Winter et al., 2019 for cultural differences in Cycling Skill Inventory).

Sample: Cycling experience. The samples of experienced cyclists prevented us from investigating to what extent cycling experience influences hazard anticipation and motor performance. Compared to results from car driving and motorcycle riding research (e.g., Horswill, 2016; Crundall et al., 2013), no evidence thus far exists about the comparison of hazard anticipation skills and its trainability among inexperienced and experienced adult cyclists.

Sample: Age. Three studies included in this dissertation sampled old participants (Chapters 5, 6, 7). The oldest participants in our studies were 80 years old. However, we recruited only a few participants with such a high age. This means that we had under-sampled the very old participants (80 years and older) who run the highest fatality risk according to road safety statistics (SWOV, 2019).

Material: Type of stimuli. The focus of this dissertation was primary on visual elements of the traffic scene as navigation through traffic is primarily a visual task. Due to the recordings of the visual material, some visual cues such as the driver's head rotation, eye contact, or hand gestures could not be investigated. In addition to visual cues, two-wheeler users also perceive auditory cues which may inform them about the presence and future action of the car driver (Stelling-Kończak, 2018). These auditory cues include sounds as engine, tire noise, and horn honking.

Material: Level of realism. Simulated environments offer high controllability and replicability. However, if the fidelity of the simulation is low, unrealistic participant responses may result (De Winter et al., 2012). With ongoing developments in high-fidelity computer-rendered traffic environments or augmented reality, future participants may be exposed to a fairly realistic experience in controlled experimental settings. Safety critical-events such as crashes can be difficult to simulate while not compromising validity.

Internet video postings taken from cameras mounted on a bicycle may be considered as a high-validity resource of accident and near-miss situations (Chapter 3). However, the non-interactive nature of video clips allows participants to allocate more resources to viewing the traffic environment than would be possible when actually controlling the bicycle.

Method: Eye-tracking. A traditional limitation of physiological measurements is their non-specific character (Näätänen & Summala, 1974). Eye-tracking measures can be used to answer ‘how’ people look but they do not provide an answer to ‘why’ people look there. In this dissertation, first an eye-tracking study (Chapter 2) was conducted to understand whether and how cyclists look at cars when approaching an intersection. As a follow-up, a video-based survey study (Chapter 3) was conducted to understand why cyclists look at the cars, i.e., which cues they use to predict what the car driver will do.

Method: Simulators. Due to the unavailability of a bicycle simulator for human-factor studies at the time of this dissertation (see Dialynas et al., 2019, for current development), the investigation of users’ braking performance in safety-critical intersection situations was conducted among motorcycle riders. Although the results are in line with our calculations of crash involvement in a video-based survey study (Chapter 3), more research using typical bicycle approach speeds (15–35 km/h) should be conducted to examine how cyclists approach an intersection.

Method: Instrumented bicycles. The field experiment reported in Chapter 5 was one of the first studies conducted on instrumented (electric) bicycles among older cyclists (see also Twisk et al., 2013). Unfortunately, sensors mounted on different bicycles did not function in the exact same way, which prevented us from conducting a statistical comparison of conventional and electric bicycles on some performance measures such as steer and roll rate. We hope that with more experience in instrumenting bicycles for field experiments as well as with improvements in the accuracy of sensors, this limitation will be overcome in future research.

Method: Self-reports. Some results in Chapters 2, 3, 4, 5 and 6 are based on self-reports. Self-reported questionnaires may suffer from biases such as due to the fact that respondents may be poorly able to consciously reflect on their cycling skills or because respondents are inclined to rate themselves as either having overly strong or weak skills (Sundström, 2008). Thus, follow-up studies to objectively evaluate self-reported behavior and performance are required (see Chapter 5). In this dissertation, the simulator study (Chapter 4) was set up to evaluate self-reported bottom-up cues (Chapter 3). Remote data collection using online survey platforms is a quick and cost-efficient form of conducting questionnaire studies but yields a relatively high percentage of meaningless responses. Thus, stringent inclusion criteria (e.g., time to complete the survey) and quality control questions have to be applied. In addition, a detailed background survey helps to understand whether the target audience was indeed recruited.

8.4. Conclusions

This dissertation provided empirical evidence concerning the hazard anticipation (tactical level) and motor performance (operational level) of cyclists and motorcyclists in safety-critical situations. The results indicated that two-wheeler users' visual focus and evasive maneuvers are governed by situational factors, especially by the speed and lateral position of the car. The prediction of a driver's right of way violation improves over time, being the most accurate when temporary closer to the conflict point. However, the results showed that there is often not enough time for the two-wheeler user to execute a successful crash avoidance action. Thus, hazard anticipation training is viable only in less-critical situations. In addition to the training of hazard anticipation skills, training programs that promote precautionary behavior and forgiving reactions may contribute to the safety of two-wheeler users at intersections. However, the 'unavoidable' accident described above could also be addressed by future engineering solutions, such as via wireless communication between vehicles or infrastructure elements.

Concerns related to the increasing popularity of electric bicycles are their higher cruising speed and their adoption among older people. In this dissertation, cycling cruising speed (measured at 15, 25, 35 km/h) was found to have a small effect on eye movements while approaching an intersection. Future research could address the effect of cycling speed on cyclists' braking behavior. This dissertation showed that older people ride their bikes (both conventional and electric) by applying additional steer and roll motions as compared to middle-aged cyclists, pointing to a difficulty in controlling the unstable bicycle. Further, certain tasks such as shoulder checks may be difficult to perform due to age-related stiffness. Engineering developments such as the development of bicycles with improved stability, or the development of feedback systems that provide information about traffic behind a cyclist could be effective in solving the difficulties that older persons face while riding a bicycle. The results in this dissertation can be used for the further origination of engineering solutions to problems that two-wheeler users face at the strategic, tactical, and operational levels.

References

- Allen, T. M., Lunenfeld, H., & Alexander, G. J. (1971). Driver information needs. *Highway Research Record*, 366, 102–115.
- Boele-Vos, M. J., Van Duijvenvoorde, K., Doumen, M. J. A., Duivenvoorden, C. W. A. E., Louwerse, W. J. R., & Davidse, R. J. (2017). Crashes involving cyclists aged 50 and over in the Netherlands: An in-depth study. *Accident Analysis & Prevention*, 105, 4–10.
- Clarke, D. D., Ward, P., Bartle, C., & Truman, W. (2007). The role of motorcyclist and other driver behaviour in two types of serious accident in the UK. *Accident Analysis & Prevention*, 39, 974–981.

- Crundall, E., Stedmon, A. W., Saikayasit, R., & Crundall, D. (2013). A simulator study investigating how motorcyclists approach side-road hazards. *Accident Analysis & Prevention*, *51*, 42–50.
- Crundall, D., Van Loon, E., Stedmon, A. W., & Crundall, E. (2013). Motorcycling experience and hazard perception. *Accident Analysis & Prevention*, *50*, 456–464.
- Cumming, R. W. (1964). The analysis of skills in driving. *Australian Road Research*, *1*, 4–14.
- De Clercq, K., Dietrich, A., Núñez Velasco, J. P., De Winter, J. C. F., & Happee, R. (2019). External human-machine interfaces on automated vehicles: effects on pedestrian crossing decisions. *Human Factors*, 0018720819836343, 1–18.
- De Winter, J. C. F., & Kováčsová, N. (2016). How science informs engineering, education, and enforcement: A message for driving instructors. In D. L. Fisher, J. Caird, W. Horrey, & L. Trick (Eds.), *Handbook of teen and novice drivers: Research, practice, policy, and directions* (pp. 31–45). Boca Raton, FL: CRC Press, Taylor & Francis Group.
- De Winter, J. C. F., Kováčsová, N., Hagenzieker, M. P. (2019). Cycling skill inventory: Assessment of motor-tactical skills and safety motives. *Traffic Injury Prevention*, 1–7.
- De Winter, J. C. F., Van Leeuwen, P. M., & Happee, P. (2012). Advantages and disadvantages of driving simulators: A discussion. In *Proceedings of Measuring Behavior* (pp. 47–50), Utrecht, The Netherlands.
- Dialynas, G., Happee, R., & Schwab, A. L. (2019). Design and hardware selection for a bicycle simulator. *Mechanical Sciences*, *10*, 1–10.
- Dozza, M., Piccinini, G. F. B., & Werneke, J. (2016). Using naturalistic data to assess e-cyclist behavior. *Transportation Research Part F: Traffic Psychology and Behaviour*, *41*, 217–226.
- Dubbeldam, R., Baten, C., Buurke, J. H., & Rietman, J. S. (2017). SOFIE, a bicycle that supports older cyclists?. *Accident Analysis & Prevention*, *105*, 117–123.
- Endsley, M. R. (1995). Toward a theory of situational awareness in dynamic systems. *Human Factors*, *37*, 32–64.
- Engbers, C., Dubbeldam, R., Buurke, J. H., Schaake, L., Goede, M. D., Rietman, J. S., & Waard, D. D. (2016). The acceptance of a prototype rear-view assistant for older cyclists: Two modalities of warnings compared. *International Journal of Human Factors and Ergonomics*, *4*, 264–281.
- European Road Safety Observatory (2006). *Pedestrians and Cyclists*. SafetyNet: European Road Safety Observatory ERSO.
- Gustafsson, P., Muñoz, J. C., Lindgren, L., Boda, C. N., & Dozza, M. (2013). BikeCOM: cooperative safety application supporting cyclists and drivers at intersections. *Proceedings of the 3rd International Conference on Driver Distraction and Inattention*, Gothenburg, Sweden.
- Hamilton-Baillie, B. (2008). Shared space: Reconciling people, places and traffic. *Built Environment*, *34*, 161–181.

- Haworth, N., & Mulvihill, C. (2005). *Review of motorcycle licensing and training* (Report no. 240). Victoria, Australia: Monash University Accident Research Centre.
- Horswill, M. S. (2016). Improving fitness to drive: The case for hazard perception training. *Australian Psychologist*, *51*, 173–181.
- Houtenbos, M. (2009). *Sociale Vergeevingsgezindheid; Een theoretische verkenning* [Social forgiveness; A theoretical exploration] (Report no. R-2009-8). Leidschendam: SWOV Institute for Road Safety Research.
- Huertas-Leyva, P., Nugent, M., Savino, G., Pierini, M., Baldanzini, N., & Rosalie, S. (2019). Emergency braking performance of motorcycle riders: skill identification in a real-life perception-action task designed for training purposes. *Transportation Research Part F: Traffic Psychology and Behaviour*, *63*, 93–107.
- Kováčsová, N., Di Gesu, M., Schwab, A. L., Gubitosa, M., Hagenzieker, M. P., & De Winter, J. C. F. (2015). A literature review on Human Factors research using motorcycle simulators. *Driving Simulation Conference DSC 2015 Europe*, Tübingen, Germany.
- Kruijer, H., Den Hertog, P., Klein Wolt, K., Panneman, M., & Sprik, E. (2013). *Fietsongevallen in Nederland. Een LIS Vervolgonderzoek naar Ongevallen met Gewone en Elektrische Fietsen* [Bicycle Crashes in the Netherlands. LIS' follow-up investigation into conventional and electric bicycles accidents]. Amsterdam: VeiligheidNL.
- Kühn, M. (2011). *Safety aspects of high-speed pedelecs*. Berlin: German Insurance Association.
- Kwan, I., & Mapstone, J. (2004). Visibility aids for pedestrians and cyclists: a systematic review of randomised controlled trials. *Accident Analysis & Prevention*, *36*, 305–312.
- MAIDS. (2009). *Motorcycle Accident In-depth Study MAIDS: In-depth investigations of accidents involving powered two wheelers* (Final Report 2.0). Brussels: The European Association of Motorcycle Manufacturers ACEM.
- Michon, J. A. (1985). A critical view of driver behavior models: What do we know, what should we do? In L. Evans & R. C. Schwing (Eds.), *Human behavior and traffic safety* (pp. 485–524). New York: Plenum Press.
- Näätänen, R., & Summala, H. (1974). A model for the role of motivational factors in drivers' decision-making. *Accident Analysis & Prevention*, *6*, 243–261.
- Penumaka, A. P., Savino, G., Baldanzini, N., & Pierini, M. (2014). In-depth investigations of PTW-car accidents caused by human errors. *Safety Science*, *68*, 212–221.
- Räsänen, M., & Summala, H. (1998). Attention and expectation problems in bicycle–car collisions: An in-depth study. *Accident Analysis & Prevention*, *30*, 657–666.
- Rissel, C., & Watkins, G. (2014). Impact on cycling behavior and weight loss of a national cycling skills program (AustCycle) in Australia 2010–2013. *Journal of Transport & Health*, *1*, 134–140.
- Rivara, F. P., & Metrik, J. (1998). *Training programs for bicycle safety*. Washington: Washington Traffic Safety Commission, Harborview Injury Prevention and Research Center.

- The Royal Society For The Prevention Of Accidents [RoSPA]. (2001). *The effectiveness of cyclist training*. Available from <http://www.rospa.com/rospaweb/docs/advice-services/road-safety/cyclists/cyclist-training-effectiveness.pdf>
- Schepers, P., & Klein Wolt, K. (2012). Single-bicycle crash types and characteristics. *Cycling Research International*, 2, 119–135.
- Schepers, P., Klein Wolt, K., Fishman, E. (2018). *The safety of e-bikes in The Netherlands* (Discussion Paper no. 2018-02). Paris: OECD Organisation for Economic Co-operation and Development, International Transport Forum.
- Segata, M., Vijeikis, R., & Cigno, R. L. (2017). Communication-based collision avoidance between vulnerable road users and cars. *3rd IEEE INFOCOM Workshop on Smart Cities and Urban Computing (SmartCity 2017)*, Atlanta, USA.
- Schleinitz, K., Petzoldt, T., Franke-Bartholdt, L., Krems, J., & Gehlert, T. (2017). The German Naturalistic Cycling Study—Comparing cycling speed of riders of different e-bikes and conventional bicycles. *Safety Science*, 92, 290–297.
- Schleinitz, K., Petzoldt, T., & Gehlert, T. (2019). Drivers' gap acceptance and time to arrival judgements when confronted with approaching bicycles, e-bikes, and scooters. *Journal of Transportation Safety & Security*, 1-14.
- Schwab, A., Hallewas, C., De Vries, H., Van de Wetering, P. (2019). *Smart motor in handlebars prevents bicycles from falling over* (Communication newsletter). Delft: TU Delft. Available from <https://www.tudelft.nl/en/2019/tu-delft/smart-motor-in-handlebars-prevents-bicycles-from-falling-over/>.
- Stelling-Kończak, A. (2018). *Cycling safe and sound: The impact of quiet electric cars, listening to music and conversing on the phone on cyclists' auditory perception and cycling safety* (Doctoral dissertation). Delft: TRAIL Research School.
- Stelling, A., Van Gent, P., De Groot, J., Twisk, D., Vlakveld, W. (2017). Naturalistic cycling study among Dutch commuter cyclists: comparing speeds on pedelecs, speed-pedelecs and conventional bikes. In *Road Safety & Simulation International Conference (RSS 2017)*, The Hague, The Netherlands.
- Stelling-Kończak, A., De Groot-Mesken, J., Vlakveld, W., Wesseling, S. (2017). *Speed-pedelec op de rijbaan: Eerste praktijkonderzoek naar gedragseffecten* [Speed pedelec on the road: The first practical research into behavioral effects] (Report no. R-2017-13). The Hague: SWOV Institute for Road Safety Research.
- Sundström, A. (2008). Self-assessment of driving skill—A review from a measurement perspective. *Transportation Research Part F: Traffic Psychology and Behaviour*, 11, 1–9.
- Swaddiwudhipong, W., Boonmak, C., Nguntra, P., & Mahasakpan, P. (1998). Effect of motorcycle rider education on changes in risk behaviours and motorcycle-related injuries in rural Thailand. *Tropical Medicine & International Health*, 3, 767–770.
- SWOV (2010). *Social forgivingness* (Fact sheet). Leidschendam: SWOV Institute for Road Safety Research.
- SWOV (2017). *Cyclists* (Fact sheet). The Hague: SWOV Institute for Road Safety Research.

- SWOV (2019). *Road deaths in the Netherlands* (Fact sheet). The Hague: SWOV Institute for Road Safety Research.
- Twisk, D. A. M., Boele-Vos, M. J., Vlakveld, W. P., Christoph, M., Sikkema, R., Remij, R., & Schwab, A. L. (2013). Preliminary results from a field experiment on e-bike safety: Speed choice and mental workload for middle-aged and elderly cyclists. *Proceedings of the 2th International Cycling Safety Conference*, Helmond, the Netherlands.
- Twisk, D., Vlakveld, W., Dijkstra, A., Reurings, M., & Wijnen, W. (2013). *From bicycle crashes to measures*. Leidschendam: SWOV Institute for Road Safety Research.
- Vlakveld, W. P., Twisk, D., Christoph, M., Boele, M., Sikkema, R., Remy, R., & Schwab, A. L. (2015). Speed choice and mental workload of elderly cyclists on e-bikes in simple and complex traffic situations: A field experiment. *Accident Analysis & Prevention*, *74*, 97–106.
- VRUITS EU. (2015, November 24). *TNO VRUITS REV - Helmond Pilot - 1920x1080 HD* [Video File]. Retrieved from <https://www.youtube.com/watch?v=cXKQ-ccxi5I>.
- Wegman, F., Zhang, F., & Dijkstra, A. (2012). How to make more cycling good for road safety? *Accident Analysis & Prevention*, *44*, 19–29.
- WHO World Health Organization (2018). *Global status report on road safety 2018*. Geneva: World Health Organization.

ACKNOWLEDGMENTS

This pile of the paper would never have been written without the support and encouragement of my supervisors, colleagues, friends, and family whom I would like to thank. I would also like to thank SWOV Institute for Road Safety Research and Siemens Industry Software NV for giving me the opportunity to conduct some research studies at their facilities.

Joost de Winter

Thank you very much for giving me a chance to experience an engineering-driven working environment and for supervising me during the entire time. Hiring a psychologist for such a position in 2014 was not an obvious choice, but I guess it worked out! I am sincerely grateful that you always found time to help me out with data analysis and for your valuable comments on my manuscripts.

Marjan Hagenzieker

You always supported me when I was unsure how to proceed or when things were getting off track. Your scientific advice helped me to put my ideas into context and to connect the dots that I initially did not see. I thank you for your invaluable advice on research planning and methodology. I admire your passion for traffic safety research and your perseverance in studying human problems before starting to evaluate technical solutions. I was honored to work with you.

Riender Happee

I would like to thank you for making possible to collaborate between two work packages during the Motorist project. I would also like to thank you for discussing research and for facilitating knowledge sharing between different projects.

Timo Lajunen

I am grateful to you for recommending me for this PhD position. I have never considered applying for a PhD and it has certainly changed my entire career path. Thank you very much!

Arend Schwab

I was impressed by your contribution to cycling science from the moment I applied for this position. It was my honor to work with you and I would like to thank you for your comments on the cycling performance studies.

Marco Pierini, Giovanni Savino, Simon Rosalie

My sincere thanks go to Marco for leading the Motorist project and to Giovanni and Simon for leading our work package research activities. Special thanks go to Simon for bringing in sport science perspective, which had a remarkable influence on the research design of our simulator study.

Willem Vlakveld

Thank you for inspiring discussions on hazard anticipation and for your guidance during cyclist hazard anticipation training study. I enjoyed working with you and I am grateful for the freedom you allowed me to have when I was developing the training.

Divera Twisk

I would like to thank you for involving me in the SWOV's cycling safety research at the beginning of my PhD journey and for discussing research during cycling safety conferences.

For now, my contribution to traffic safety research ends. However, I will always now and then open Google Scholar to see your great research studies!

Zhenji, Felix, Maria, Peter, Carlos, and Oliver

So many things to say! I am thankful that our paths have crossed and that it always ends up with some kind of funny story. I do miss our coffee and beer breaks as well as our lunch and dinner breaks during those countless long working hours. Without you, I would never have become aware of the shoes business, the apple diet, that making a poster can be fun, that ogenbewegingenregistratieapparaat can be used for eye tracking, the existence of 864 emotions, and all the fancy engineering terms that I no longer remember.

George, Pavlo, Martijn, Christopher, Renato, Miltos, Laura, Jork, Tugrul, Barys, and others

Specials thanks go to my office mates and other colleagues from 3mE and CoR for creating a stimulating working environment where we could share our knowledge, perspectives, and cultural experience.

Maria, Marco, Francesco, Pedro, Gustavo, Marilee, Raul, Mohammad, Siamak, Lukáš, Sounak, and Tomasz

I was lucky enough to be part of the Marie Curie project: Motorist. Working with people with different backgrounds on the project with one overreaching goal was for me a valuable experience. I would like to thank you all for the time and work we shared together. Good luck in your future endeavors and I'll hopefully see you somewhere around the world!

Agnieszka, Marjolein, Michiel, Saskia, Celina, Simone, Sander, Ana, and others

I am grateful to the researchers at SWOV for welcoming me there and for always being available to answer my questions and to help me with conducting my research studies.

ACKNOWLEDGMENTS

Jochen, Taeke, Rick, Stijn, Rutger, Franco, Pepijn, Robert, Alan, Hank, Coen, and others

It was my pleasure to work with you during your bachelor projects and internships. I am glad that your work significantly contributed to some chapters in this thesis.

My colleagues at DNV GL

I would like to thank you for your support during the last stage of this PhD journey.

My friends, my family

I express my most sincere gratitude to you for making my life outside academia full of fun and joy.

LIST OF PUBLICATIONS

Journal papers

- De Winter, J. C. F., Kováčsová, N., & Hagenzieker, M. P. (2019). Cycling skill inventory: Assessment of motor-tactical skills and safety motives. *Traffic Injury Prevention*, 1–7.
- Kováčsová, N., Cabrall, C. D. D., Antonisse, S. J., de Haan, T., van Namen, R., Nooren, J. L., Schreurs, R., Hagenzieker, M. P., & De Winter, J. C. F. (2018). Cyclists' eye movements and crossing judgments at uncontrolled intersections: An eye-tracking study using animated video clips. *Accident Analysis & Prevention*, 120, 270–280.
- Kováčsová, N., De Winter, J. C. F., & Hagenzieker, M. P. (2019). What will the car driver do? A video-based questionnaire study on cyclists' anticipation during safety-critical situations. *Journal of Safety Research*, 69, 11–21.
- Kováčsová, N., De Winter, J. C. F., Schwab, A. L., Christoph, M., Twisk, D. A. M., & Hagenzieker, M. P. (2016). Riding performance on a conventional bicycle and a pedelec in low speed exercises: Objective and subjective evaluation of middle-aged and older persons. *Transportation Research Part F: Traffic Psychology and Behaviour*, 42, 28–43.
- Kováčsová, N., Grotoli, M., Celiberti, F., Lemmens, Y., Happee, R., Hagenzieker, M. P., & De Winter, J. C. F. (2020). Emergency braking at intersections: A motion-base motorcycle simulator study. *Applied Ergonomics*, 82, 102970.
- Kováčsová, N., Vlakoveld, W. P., De Winter, J. C. F., & Hagenzieker, M. P. (2020). PC-based hazard anticipation training intervention for experienced cyclists: Design and evaluation. *Safety Science*, 123, 104561.

Book chapter

- De Winter, J. C. F., & Kováčsová, N. (2016). How science informs engineering, education, and enforcement: A message for driving instructors. In D. L. Fisher, J. Caird, W. Horrey, & L. Trick (Eds.), *Handbook of teen and novice drivers: Research, practice, policy, and directions* (pp. 31–45). Boca Raton, FL: CRC Press, Taylor & Francis Group.

Conference proceedings

- De Winter, J. C. F., Kováčsová, N., & Hagenzieker, M. P. (2017). Cycling Skill Inventory: Assessment of motor-tactical and safety skills. Proceedings of the *7th International Cycling Safety Conference*, Barcelona, Spain.
- Kováčsová, N., De Winter, J. C. F., Schwab, A. L., & Hagenzieker, M. P. (2014). Factors contributing to pedelec crashes in the Netherlands. Proceedings of the *3rd International Cycling Safety Conference*, Gothenburg, Sweden.
- Kováčsová, N., Di Gesu, M., Schwab, A.L., Toso, A., Gubitosa, M., Hagenzieker, M.P., & De Winter, J.C.F. (2015). A literature review on Human Factors research using

motorcycle simulators. Poster presented at the *Driving Simulation Conference & Exhibition 2015 (DSC 2015 Europe)*, Tübingen, Germany.

- Kováčsová, N., De Winter, J.C.F., Schwab, A.L., Twisk, D.A.M., & Hagenzieker, M.P. (2016). Riding performance on a conventional bicycle and an e-bike during three low-speed exercises: Comparing middle-aged with older cyclists. Presented at the *International Conference on Traffic and Transport Psychology 2016 (ICTTP 2016)*, Brisbane, Australia.
- Bazilinskyy, P., Kováčsová, N., Jawahiri, A.A., Kapel, P., Mulckhuysen, J., Wagenaar, S., & De Winter, J.C.F. (2016). Object-alignment performance in a head-mounted display versus a monitor. Conference paper submitted to *SMC IEEE 2016*, October, Budapest, Hungary.
- Kováčsová, N., Cabral, C. D. D., Antonisse, S. J., De Haan, T., Van Namen, R., Nooren, J. L., Schreurs, R., Hagenzieker, M. P., & De Winter, J. C. F. (2016). Cyclists' eye movements at uncontrolled intersections: An eye-tracking study using animated video clips. Proceedings of the *5th International Cycling Safety Conference*, Bologna, Italy.
- Kováčsová, N., De Winter, J. C. F., & Hagenzieker, M. P. (2017). Cyclists' predictions of what a car driver will do next at intersections. Proceedings of the *6th International Cycling Safety Conference*, Davis, California, USA.
- Kováčsová, N., Vlakveld, W. P., De Winter, J. C. F., & Hagenzieker, M. P. (2018). Development and evaluation of a PC-based hazard anticipation training for cyclists. Proceedings of the *7th International Cycling Safety Conference*, Barcelona, Spain.

Reports

- Huertas-Leyva, P., Savino, G., Baldanzini, N., Kováčsová, N., De Winter, J. C. F., DiGesù, M., Toso, A., Donders, S., & Gubitosa, M. (2015). *Identification of rider training strategies* (MOTORIST deliverable no. D1.1). Retrieved from http://www.motorist-ptw.eu/?page_id=2068.
- Kováčsová, N., Grotoli, M., Celiberti, F., Lemmens, Y., Happee, R., Hagenzieker, M. P., & De Winter, J. C. F. (2018). *Report on rider training on a motorcycle test rig* (MOTORIST deliverable no. D1.3). Retrieved from http://www.motorist-ptw.eu/?page_id=2068.
- Kováčsová, N., & De Winter, J. C. F. (2017). *Rider training: Testing and evaluation* (MOTORIST deliverable no. D1.4). Retrieved from http://www.motorist-ptw.eu/?page_id=2068.

Workshop presentation

- Kováčsová, N., Di Gesù, M., De Winter, J.C.F., Lemmens, Y., & Liefoghe, C. (2016). The MOTORIST simulator: Experimental setup and testing activities. Presented at

Safe2Wheelers - Accidentology and Motorcycle Simulator Workshop 2016, Wurzburg, Germany.

Datasets and related documents

De Winter, J. C. F., Kováčsová, N., & Hagenzieker, M. P. (2019). *Supplementary data for the article: Cycling Skill Inventory: Assessment of motor-tactical skills and safety motives* [Dataset, Scripts]. 4TU.Centre for Research Data. Retrieved from <https://doi.org/10.4121/uuid:daec0b0a-17fc-425b-988c-d55c4fae476a>.

Kováčsová, N., Cabrall, C. D. D., Antonisse, S. J., de Haan, T., van Namen, R., Nooren, J. L., Schreurs, R., Hagenzieker, M. P., & De Winter, J. C. F. (2018). *Supplementary data for the article: Cyclists' eye movements and crossing judgments at uncontrolled intersections: An eye-tracking study using animated video clips* [Stimuli material, Dataset, Experiment-related forms, Scripts]. 4TU.Centre for Research Data. Retrieved from <https://doi.org/10.4121/uuid:1d8ddcd0-5139-4ada-81a1-9f34c9f70c88>.

Kováčsová, N., De Winter, J. C. F., & Hagenzieker, M. P. (2019). *Supplementary data for the article: What will the car driver do? A video-based questionnaire study on cyclists' anticipation during safety-critical situations* [Dataset, Questionnaire, Supplementary material]. 4TU.Centre for Research Data. Retrieved from <https://doi.org/10.4121/uuid:b44bed89-3b9a-48fb-8758-6e2bb0d7ec72>.

Kováčsová, N., Grotoli, M., Celiberti, F., Lemmens, Y., Happee, R., Hagenzieker, M. P., & De Winter, J. C. F. (2020). *Supplementary data for the article: Emergency braking at intersections: A motion-base motorcycle simulator study* [Supplementary material, Illustrative video of the experiment, Scripts, Vehicles' s profiles and simulated world characteristics, Oculus Rift settings, and questionnaire data]. 4TU.Centre for Research Data. Retrieved from <http://doi.org/10.4121/uuid:6b1e0ffb-3606-4095-9702-be34dd3c2d59>.

Kováčsová, N., Vlakveld, W. P., De Winter, J. C. F., & Hagenzieker, M. P. (2020). *Supplementary data for the article: PC-based hazard anticipation training intervention for experienced cyclists: Design and evaluation* [Supplementary analyses and stimuli material].

CURRICULUM VITAE

NATÁLIA KOVÁČSOVÁ

Born in Galanta, Slovakia, 3rd January 1990.

Education

- 2014 – 2020 Delft University of Technology, The Netherlands
Faculty of Mechanical, Maritime and Materials Engineering,
Department of BioMechanical Engineering
PhD in Human Factors (Recipient of Marie Skłodowska-Curie European Fellowship)
- 2013 Norwegian University of Science and Technology, Norway
Faculty of Social and Educational Sciences, Department of Psychology
Visiting Scholar (Recipient of Slovak National Scholarship)
- 2011 – 2013 Comenius University in Bratislava, Slovakia
Faculty of Arts, Department of Psychology
MSc in Psychology
- 2008 – 2011 Comenius University in Bratislava, Slovakia
Faculty of Arts, Department of Psychology
BSc in Psychology

